# Conservation and Distributional Consequences of Pricing Scarce Water During Droughts*

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**Abstract**

Using incentives to allocate scarce goods is a core tenet of environmental economics but may result in unpalatable distributional outcomes. We analyze surcharges enacted during a severe drought in Southern California within nonlinear rate structures. Using machine learning to generate counterfactual predictions, we find surcharges lead to limited water conservation despite steep price increases. "Budget-based" rates counteract conservation goals by shielding large users from high prices and surcharges do little to reduce the regressivity of water expenditures. Simpler rate structures can dominate along equity dimensions and their progressivity can be enhanced via lump-sum transfers within the rate structure.

**JEL codes:** D12, H42, L95, Q25

**Key Words:** Conservation policy; drought management; nonlinear pricing; water demand

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# 1 Introduction

Severe droughts linked to climate change threaten water supplies globally. Water scarcity is particularly acute in the western United States, a region currently experiencing its driest conditions since at least 800 C.E. (Williams et al., 2022). Extended drought periods place tremendous pressure on urban water districts, especially those without their own surface or groundwater rights that rely on purchased water deliveries. In the face of shrinking and uncertain supply, water managers in arid regions must continue to search for policy instruments to curb residential water demand.

Economists often advocate for raising the price of water to reflect its scarcity value. However, multiple factors inhibit water prices from adjusting to real-time supply conditions. First, economies of scale in piped water provision cause most residential water in the U.S. to be supplied by a single local municipal utility with administratively set water prices.[1] Changing prices often requires a formal ratemaking process and cannot quickly adjust to match real-time supply fluctuations during drought (Hanemann, 1997). Additionally, the recognition of water access as a human right (UN General Assembly, 2010) coupled with political pressure means that water prices often fall below the long-run marginal cost of supply (Timmins, 2002a,b; Renzetti, 1992, 1999). Such systematic under-pricing fails to adequately signal to households the scarcity value of the water they consume (Olmstead, 2010).[2] Even though water is theoretically under-priced, implementing price increases raises equity concerns. At least 10% of U.S. households currently grapple with water affordability issues, which have been exacerbated by the COVID-19 pandemic (Bostic et al., 2021; Cardoso and Wichman, 2022).

Given the tension between sending appropriate scarcity signals and maintaining affordability, how can residential water rates jointly address conservation and equity objectives during times of severe drought? We address this question by studying the performance of two drought surcharge pricing programs layered within existing rate structures. Our sample covers the 2011–2017 period in California, during which the state experienced some of its driest years in recorded history (Mount et al., 2023). In 2015, utilities facing unprecedented conservation mandates from the state adopted a variety of price and non-price policies to induce dramatic decreases in water consumption. The two utilities that we consider implemented temporary surcharge price increases in 2015 through large inframarginal and marginal price changes within their existing nonlinear "budget-based" rate structures, or BBRs, that define household-specific consumption tiers. BBRs are similar to traditional increasing-block rates (IBRs) where the marginal price for consuming an additional unit of water rises as consumption increases. The key difference between BBRs and

[1]Nearly 90% of community water systems in the United States are public. Source: https://efc.web.unc.edu/2016/10/19/public-vs-private-a-national-overview-of-water-systems/. Last accessed: May 16, 2024.

[2]Municipal utilities are also generally further constrained by revenue recovery requirements, which limit utilities to recovering revenues adequate to cover their costs of supplying water. This is especially true in California due to Proposition 218, which limits the types of fees that local governments (including water utilities) can assess. Wang and Wolak (2022) investigate how nonlinear prices can be used to reduce system-wide uncertainty in revenue generation.

their IBR counterparts is the assignment of individualized water budgets to each household that also vary month-to-month. These individualized budgets directly determine the marginal price tiers a household faces, as opposed to IBRs where the consumption tiers that define prices are the same for all households.

Using a panel of monthly bills for over 37,000 households, we estimate a series of demand models to characterize how households responded to drought surcharges. To isolate the effect of price increases on water use from a suite of other non-price policies, information campaigns, and behavioral nudges adopted contemporaneously, we develop an approach to generate counterfactual consumption estimates during the drought surcharge period. We build on the framework of Burlig et al. (2020) and Prest et al. (2023) by using random forests to generate predictions for what consumption would have been during the drought surcharge period absent any policy changes. We then use our counterfactual predictions to construct an instrument for price in our demand models. This simulated instrument—the difference between the predicted price a household faces under surcharge pricing and the predicted price a household would have faced for the same level of consumption prior to surcharge pricing—isolates the exogenous policy-induced variation in prices needed to estimate causal price elasticities (Ito, 2014; Sears, 2021; Ito and Zhang, 2023).

Our primary price elasticity estimates range from -0.2 to -1.0 and are largely consistent with those reported in the broader water demand literature (Espey et al., 1997; Dalhuisen et al., 2003). This is true even though our setting is relatively rare in that we isolate exogenous variation in *temporary* drought surcharges, as opposed to permanent changes in the rate structure. These results suggest that drought surcharges fail to induce elastic price responses even under severe drought.[3] We conduct a series of simulation exercises where we combine our demand estimates with the total water conservation observed in our data to identify what proportion of observed conservation can be attributed directly to the drought surcharges themselves. Under reasonable assumptions, we find that the surcharges are only able to explain around one-third or less of the aggregate conservation. This result has important implications for urban water managers, as it emphasizes the role that both price and non-price policy instruments play in curbing residential water demand (Olmstead and Stavins, 2009; Wichman et al., 2016; Browne et al., 2021).

We then decompose which consumers bear the burden of drought surcharge pricing. It is well-established that water bills in general are a regressive means of raising revenue when compared to other public funding mechanisms that directly target wealth such as income or property taxes (Cardoso and Wichman, 2022). We confirm that the BBRs observed here are regressive by plotting observed water expenditure shares across income groups, finding that the lowest-income groups pay the largest proportion of their total income for water. While this regressivity is not specific to the BBRs observed here, in theory surcharge pricing could result in some redistribution if high-income, high-use households face steep price increases. We investigate this by

[3] These results are also consistent with evidence from the energy demand literature showing that demand elasticities for electricity remain consistent even in the face of extreme energy price changes (Alberini et al., 2019).

constructing Lorenz curves of water expenditures and income in a manner inspired by Levinson and Silva (2022). We find that drought surcharges induce little change in regressivity even under optimistic assumptions about consumer price-responsiveness. Further investigation reveals that while surcharges do affect households who exceed their assigned water budget, the assignment of budgets using factors such as lawn size shields large water users from facing the highest marginal price tiers. This implies that the BBRs we consider here both weaken the scarcity signal intended to be sent by surcharge pricing and implicitly transfer some costs to smaller, poorer homes. We find that BBRs subsidize nonessential water demand by providing more cheap water to households expected to have large demands for water (like those with large lawns).[4]

Lastly, we simulate how alternative rate structures under surcharge pricing would affect equity considerations. Using our counterfactual consumption predictions, we construct household water bills under several hypothetical rate structures. We find that uniform rate structures perform similarly or slightly worse to BBRs in terms of equity, but pairing the uniform rate with a variable service charge tied to observable measures of income or wealth largely ameliorates the equity concerns. Additionally, we find that BBRs are more regressive than their IBR counterparts. As a result, it may be preferable for utilities to employ simpler rate structures given that consumers often misperceive complex nonlinear prices (Ito, 2014; Wichman, 2014; Brent and Ward, 2019; Shaffer, 2020). Although we conclude that BBRs do not offer equity advantages over stylized alternatives, water budgets combined with drought surcharges do retain the ability to transmit household-specific information signals about what the utility considers to be "wasteful" consumption. An understanding of whether these signals serve as an effective non-price conservation tool is needed to make definitive claims about the ultimate welfare performance of BBRs relative to hypothetical alternatives.

Our findings contribute to several distinct literatures. First, we introduce new evidence to the rich economics literature on the demand for residential water (e.g., Howe and Linaweaver Jr, 1967; Espey et al., 1997; Dalhuisen et al., 2003). Modern studies estimate causal price elasticities for water demand using a panel of billing microdata and quasi-experimental variation in prices (Nataraj and Hanemann, 2011; Wichman, 2014; Wichman et al., 2016; Sears, 2021). Our study is unique in that we identify responses to temporary surcharge price increases and find largely inelastic demand, as opposed to the more common case in the literature of permanent rate changes. This finding is relevant for utilities pursuing adaptive water management that allow prices to temporarily reduce consumption during droughts. We also add to the literature estimating the impact of price and nonprice water conservation policies implemented during the California drought of 2011-2017. These include nudges like home water reports (Ferraro and Price, 2013; Brent et al., 2015, 2020; Jessoe et al., 2021; Brent and Wichman, 2022), public shaming and moral suasion (Sears, 2021), fees and other excess water use fines (Sears, 2021; Pratt,

[4]Given evidence that peer effects associated with the conversion from green to dry landscaping are a key mechanism driving urban water conservation efforts, assigning household water budgets that increase with lawn size could potentially inhibit further adoption of such landscaping practices by large-lawn, high-income households (Bollinger et al., 2020).

2023), and automated irrigation enforcement (West et al., 2021; Browne et al., 2023). Our analysis of conservation effects of price during drought is similar to Browne et al. (2021), who study price increases in Fresno during the drought. Our study has the advantage of isolating exogenous variation in exposure to price increases to identify causal price responses, and the resulting distributional effects, while Browne et al. (2021) only present correlations due to limited price variation. Given that drought conditions are expected to persist under worsening climate conditions, it is crucial to understand which drought policies implemented in California were effective at inducing conservation. Our study contributes an important analysis of surcharge pricing that can help inform future policy design.

Second, we contribute to the literature considering the distributional impacts of environmental policy broadly, and specifically the ability of utility rates to serve as a redistributive policy instrument to meet equity goals (e.g., Borenstein, 2012; Borenstein and Davis, 2012; Deryugina et al., 2019; Brolinson, 2020; Burger et al., 2020; Levinson and Silva, 2022). Much of this literature is focused on prices for electricity or natural gas, with fewer papers studying the redistributive aspects of water prices despite their acute importance to low-income households. Olmstead and Stavins (2009) discuss the importance of considering the equity properties of prices as a conservation instrument as opposed to nonprice policies, noting that neither has a theoretical advantage over the other in terms of equity. Recent studies have addressed equity more directly, finding that seasonal rates may induce larger conservation responses in wealthier, higher-use homes and that individualized rates based on average winter consumption may be regressive under certain conditions (El-Khattabi et al., 2021; Smith, 2022). Our study is unique in that it unpacks the distributional implications of nonlinear water rates specifically in the context of surcharge pricing under drought conditions. Our analysis also further complements Burger et al. (2020) and proposals for more progressive electricity rates such as Borenstein et al. (2021) by illustrating the desirable equity benefits of allowing fixed charges to vary with household income. Given the expected persistence of drought conditions combined with rising concerns over water affordability, further analysis of the equity implications of water prices is crucial (Mack and Wrase, 2017; Cardoso and Wichman, 2022; Wichman, 2023).

Third, we contribute to a growing literature on behavioral responses to household-specific nonlinear water rates that have rapidly increasing penetration in arid regions (Mayer et al., 2008; Barr and Ash, 2015). While a rich literature exists on nonlinear pricing broadly, relatively few papers consider budget-based rates specifically. Baerenklau et al. (2014) estimate large reductions in demand due to the introduction of budget-based rates in a southern California utility. Other studies also find that budget-based rates can induce conservation, particularly in high-use households through information signals sent by individualized budgets (Baerenklau and Pérez-Urdiales, 2019; Pérez-Urdiales and Baerenklau, 2019). Other papers in this literature study demand responses to individualized water rates that are similar in practice to budget-based rates, but with tiers defined using other metrics such as average winter consumption or annual cumulative consumption (Smith, 2022; Li and Jeuland, 2023). While our focus is on drought surcharges, our results stand in contrast to the literature on individualized water rates and suggest a more nuanced view of BBRs. Although BBRs are often hailed as progressive, through our distributional analysis we highlight potential equity concerns associated with the implicit subsidies that BBRs grant to households with larger outdoor lawns.

Finally, we contribute to the literature combining machine learning methods with traditional program evaluation tools (Mullainathan and Spiess, 2017; Athey and Imbens, 2019). Within economics, predicting missing counterfactuals is a particularly useful application of machine learning, and various predictive methods have been shown to work well in the context of energy and water demand (Burlig et al., 2020; Athey et al., 2021; Prest et al., 2023). We demonstrate how out-of-sample predictions from machine learning models can be used to define an exogenous instrument in an instrumental variables framework, which is then used to estimate causal price elasticities. Given the growing evidence that machine learning tools can replicate benchmark treatment effects from randomized experiments (Prest et al., 2023), approaches like ours will become increasingly more common given the costly and difficult nature of successfully designing and implementing randomized experiments within these settings.

## 2 Background: Water Rates Under Drought of 2011-2017

California is notorious for its highly variable climate, with both wetter-than-average and drier-than-average years occurring regularly (Mount et al., 2021). California entered into an extended period of drier-than-average conditions in the latter half of 2011, and by mid-2012 large swaths of the state were experiencing at least ”moderate drought” (NOAA, 2023). In response to the extended drought conditions, Governor Brown declared a state of emergency on January 17, 2014. The order directed state resources towards water conservation campaigns and called on Californians to reduce water consumption by 20%.

With drought conditions persisting and water scarcity concerns growing increasingly more severe, on April 1, 2015 Governor Brown issued a second executive order that took the unprecedented step of ordering mandatory statewide water cuts from urban water suppliers. Specifically, the order directed the State Water Resources Control Board to impose restrictions that would achieve a 25% reduction in statewide urban water consumption relative to 2013 levels. The order also established a permanent water consumption and conservation reporting requirement for urban water suppliers. These mandatory urban water cuts spurred urban utilities to adopt a variety of price and non-price policy interventions, and were in effect for a year until their withdrawal in May 2016.

California entered into an especially wet period in water year 2017 (starting in October 2016). Specifically, January and February 2017 were the wettest months on record for some parts of the state, including the northern Sierra Nevada mountain range and the San Joaquin River basin (NOAA, 2017). These unusually high precipitation levels (including snowfall) helped replenish surface water levels at critical reservoirs, while at the same time inflicting significant economic damage due to flooding. The increased precipitation levels, combined with evidence that urban water suppliers were succeeding to some degree at inducing conservation, caused the lifting of the drought state of emergency on April 7, 2017.[5]

### 2.1 Nonlinear Rate Structures

We study the nonlinear rate structures of two water utilities in southern California, both of which provide drinking water and sewer services to dedicated residential service areas. Both utilities are heavily dependent on imported water sourced from the Sacramento-San Joaquin Bay-Delta (through the State Water Project) and the Colorado River (by way of the Colorado River Aqueduct), though one utility does hold limited groundwater rights. The first utility serves an area closer to the Pacific Coast with a relatively denser population, smaller lot sizes on average and a relatively cooler climate. The second utility serves an area that is further inland with a relatively less-dense population, larger lot sizes and a relatively warmer climate. Hence, we refer hereafter to the first utility as the Coastal Utility and the second utility as the Inland Utility. As part of a data-sharing agreement, we refrain from publicly identifying the two utilities here.

Both utilities price water through a BBR. BBRs are similar to traditional IBRs in that the marginal price for consuming an additional unit of water rises as households consume higher quantities. The key difference between BBRs and their IBR counterparts is the assignment of individualized water budgets to each household that also vary month-to-month. These individualized budgets directly determine the marginal price tier a household faces, as opposed to IBRs where the consumption tiers that define prices are common to all households. For example, in a simple IBR with a low and high price all households will pay the high price for units above the common threshold $k$. In a BBR, each household $i$ has their own threshold, $k_i$, that depends on household and weather characteristics and is determined by a water budget formula. Both utilities use roughly similar water budget formulas that define a two-part budget consisting of indoor and outdoor components. Together, the indoor and outdoor budgets define what the utility views as acceptable or non-"wasteful" water consumption for a household in a given month.

Equation 1 outlines the calculation of household $i$'s indoor water budget in billing period $t$:

$$Indoor_{it} = Persons_i \times GPCD_t \times Days_{it} \times (1/748) \tag{1}$$

In Equation 1, *Persons* is the household size, *GPCD* is an allotment made by the utility for water usage in gallons per capita per day, *Days* is the number of days in the billing cycle, and (1/748) is a scaling factor to convert from gallons of water to hundred cubic feet (1 CCF = 748 gallons). Coastal Utility assumes a household size of four for single-family residential homes and three

[5] Figure A.1 lays out a visual timeline of the events discussed in this section. More information on both the 2014 and 2015 executive orders can be found at `https://www.ca.gov/archive/gov39/2014/01/17/news18368/index.html` and `https://www.ca.gov/archive/gov39/2015/04/01/news18913/index.html`, respectively. Information on the 2017 lifting of the state of emergency can be found at: `https://www.ca.gov/archive/gov39/2017/04/07/news19748/index.html`. Last accessed: January 15, 2024.

for condominiums, while Inland Utility assumes a household size of three for all residential customers.[6] Coastal allotted 65 GPCD through April 2015, and then 60 GPCD through the end of our study period. Inland used a value of 60 GPCD throughout the study period.

Equation 2 outlines the calculation of household $i$'s outdoor water budget in billing period $t$:

$$Outdoor_{it} = Area_i \times ET_{it} \times PF_{it} \times (0.62/748) \tag{2}$$

In Equation 2, *Area* is the amount of irrigable area on the customer's property in square feet, *ET* is a measure of monthly evapotranspiration in inches, *PF* (Plant Factor) is a constant assumed by the utility about the types of vegetation present on a given property and the subsequent amount of water required, and (0.62/748) is a scaling factor to convert from inches to gallons/square foot, and then to CCF. Households can also request to update the amount of irrigable square footage used to calculate their outdoor budget. Coastal assigns a constant value for plant factor across households and months (0.8 before April 2015 and 0.7 after), while Inland assigns varying plant factors depending on the month and service start date. A household's total water budget is determined by summing the indoor and outdoor water budgets (i.e., $Budget_{it} = Indoor_{it} + Outdoor_{it}$). In practice, household size and irrigable area drive between-household variation in water budgets, while evapotranspiration drives both between-household variation in budgets (across the spatial landscape) as well as within-household variation (over the course of the year).

## 2.2 Implementing Drought Surcharges within Nonlinear Rates

Figure 1 displays visually the nominal nonlinear prices and consumption tiers over time under each utility's BBR structure. Water use within the customer's indoor budget is charged at the lowest marginal prices. Consumption above the indoor water budget but still below the total budget is charged at the Tier 2 price, representing outdoor consumption. Any consumption above this is considered "over budget" and is charged at the relatively higher tier prices. 125% and 150% of total budget are the relevant thresholds between Tiers 3 and 4 consumption and Tiers 4 and 5 consumption, respectively. Coastal uses five price tiers and kept rates constant through April 2015, when it lowered the marginal price in its highest tiers. Inland implemented several small increases over time. Inland also only used four price tiers for its first year of BBR implementation, adding a fifth tier in October 2012. Coastal has a higher peak-to-minimum marginal price ratio than Inland, with the highest marginal price being more than four to five times greater than the lowest marginal prices over the course of the study period.

Figure 1 also illustrates how the two utilities responded to worsening drought conditions without changing the underlying rate structure. Following the April 2015 executive order mandating 25% water cuts statewide, both Coastal and Inland entered into elevated stages of their water shortage contingency plans (WSCP). A crucial aspect of each utility's drought response

[6] It is the responsibility of the household to contact the utility to update household size, and verification is handled on a case-by-case basis. In Appendix D we demonstrate how these household size assumptions end up over-allocating water to many households by overestimating the number of persons in the home.

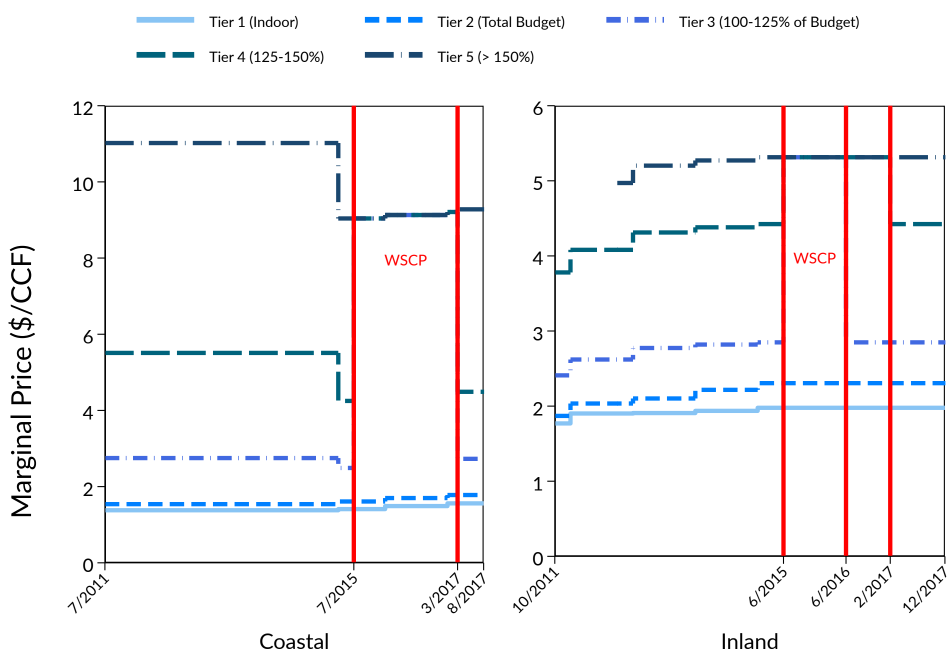



Figure 1: Rate Structures Over Time

**Notes:** The figure presents the nonlinear budget-based rate structures in place for each utility over the course of the study period that we observe. Marginal prices are given in nominal U.S. dollars/centum cubic feet ($/CCF). The solid red vertical bars represent the period during which each utility's drought surcharges were in effect, invoked under their water shortage contingency plans.

strategy under their WSCP was the imposition of drought surcharges on over-budget water users. Both utilities implemented such drought surcharges from the summer of 2015 until February 2017. Under their WSCP, Coastal suspended the Tier 3 and 4 prices, and assessed a $7.43/CCF charge on all consumption over a household's water budget, the difference between the Tier 2 and Tier 5 price. For the first year under their WSCP, Inland similarly suspended Tier 3 and Tier 4 rates. Inland also reduced outdoor water budgets by 30% during this time. From June 2016 until the surcharges were lifted in February 2017, Inland restored outdoor water budgets and the Tier 3 price, and charged all consumption over 125% of budget at the Tier 5 level. Drought surcharges are represented in Figure 1 by removing the intermediate tier prices when the WSCP was in effect, denoted by the red vertical bars. In practice, moving from 100% to 101% of a household's budget during the WSCP results in dramatic increase in marginal prices.

Throughout the paper, we refer to the price changes observed here as drought surcharges, as opposed to the more traditional idea of conservation prices. Under conservation pricing, rates are designed to permanently recover the lost revenue that results from selling less water over the long-run. Drought surcharges are designed to be temporary in nature and are not intended to raise revenues through the highest tiers, only to cover the costs associated with purchasing higher-cost water supplies under drought. The drought surcharges implemented here sought to communicate scarcity through the household budget and discourage excessive and potentially wasteful consumption by having households face the highest tier prices immediately after going over-budget, while still preserving low marginal prices for under-budget consumption. Both utilities underwent extensive campaigns to warn households about the impending drought surcharges and to encourage within-budget consumption. The surcharges were carefully implemented in accordance with Proposition 218 restrictions that impact how utilities can price water under nonlinear rate structures.[7] In both utilities, any excess revenues generated above the marginal cost of water supply were directly recycled back into water efficiency programs.

## 3 Data

We make use of four primary data sources in our analysis: household-level monthly billing data, demographic information from the U.S. Census Bureau, property value and tax information from county assessor offices, and local weather data. We obtain our monthly water billing records from the California Data Collaborative (CaDC), a data nonprofit focused on water issues in California. For both utilities, we restrict the data to include only single-family residential customers for which we have a full or nearly-full panel ($\geq$ 70 months) of billing records since the time when BBRs went into effect (July 2011 for Coastal, October 2011 for Inland). After further cleaning and imposition of filters such as dropping extreme outliers, we are left with 1,989,521 customer-month observations for Coastal (27,006 unique households) and 789,741 observations for Inland (10,181 unique households). A complete description of the data cleaning steps is provided in Appendix B. We merge prices to these data using publicly available rate information.

We supplement our billing microdata with data from three additional sources. First, we obtained demographic information on the distribution of household size, race and income distributions at the census block group level from the U.S. Census Bureau's American Community Survey (ACS) 2015 5-year estimates (U.S. Census Bureau, 2015). We match households to census block groups using the block group information provided in the billing records. Second, we obtain assessor data for the two California counties in which the utilities are located. These records include the property values (land and improvement value) and other property characteristics such as the total area of the lot, the number of bedrooms and bathrooms of the structure, and detailed property use code descriptions.

Finally, we obtain data on local weather beyond evapotranspiration (which was included in the billing data for the purpose of calculating water budgets). We use high-resolution weather data from the Parameter-elevation Relationships on Independent Slopes model (PRISM) and the panel of daily weather observations across our entire study period used in Schlenker and

[7] At least one municipal utility has been forced to alter its nonlinear rate structure in response to Proposition 218 concerns. See *Capistrano Taxpayers Association, Inc. v. City of San Juan Capistrano*, 236 Cal.App.4th 1123 (Cal. Ct. App. 2015). The case held that nonlinear water rates did not inherently violate Proposition 218, but that tier definitions must be informed by the actual cost of supplying water service in each tier.

Roberts (2009) to construct average minimum and maximum temperature, as well as average and total precipitation over the course of the billing period for each customer-month. We match our households to the 2.5-by-2.5-mile grids using household latitude and longitude provided in the billing records. We also use data from the California Irrigation Management Information System (CIMIS) for some records in Inland where evapotranspiration and/or outdoor water budget amounts were missing (CIMIS, 2018).

Table 1: Summary Statistics

| Coastal | Mean | Std. Dev. | Inland | Mean | Std. Dev. |
|---|---|---|---|---|---|
| Water Consumption (CCF) | 12.77 | 9.85 | Water Consumption (CCF) | 24.57 | 20.83 |
| Indoor Water Budget (CCF) | 10.11 | 2.07 | Indoor Water Budget (CCF) | 9.40 | 3.61 |
| Outdoor Water Budget (CCF) | 7.29 | 8.09 | Outdoor Water Budget (CCF) | 30.51 | 37.49 |
| Monthly Water Budget (CCF) | 17.40 | 8.88 | Monthly Water Budget (CCF) | 39.91 | 37.88 |
| Household Size | 3.96 | 0.73 | Household Size | 4.07 | 1.41 |
| Gallons per capita per day | 63.05 | 2.44 | Gallons per capita per day | 60.00 | 0.00 |
| Days in billing period | 30.46 | 2.80 | Days in billing period | 30.39 | 3.58 |
| Irrigable Square Feet | 2,717.04 | 2,745.27 | Irrigable Square Feet | 8,810.87 | 8,834.65 |
| Evapotranspiration (inches) | 4.16 | 1.33 | Evapotranspiration (inches) | 5.25 | 1.92 |
| No. of bedrooms | 2.53 | 1.59 | No. of bedrooms | 3.91 | 0.79 |
| Property Value (1000 USD) | 485.37 | 329.02 | Property Value (1000 USD) | 388.19 | 144.85 |
| Unique Accounts | 27,006 | | Unique Accounts | 10,841 | |
| Total Billing Observations | 1,989,521 | | Total Billing Observations | 789,741 | |

**Notes:** The table presents billing-record level summary statistics for each utility separately. Summary statistics are presented for the full period of billing records available: July 2011–August 2017 for Coastal and October 2011–December 2017 for Inland.

We present in Table 1 billing-record level summary statistics of key variables related to consumption, budgets, and property characteristics for the households in our data. Households in Inland tend to be larger homes, both in terms of actual dwelling size (e.g. number of bedrooms) and in terms of lot size (e.g. irrigable square footage). Households in Inland have roughly triple the amount of irrigable square footage of homes than in Coastal (on average). Recall that irrigable square footage is a direct component of the water budget calculation formula, and thus leads to higher average outdoor and total budgets in Inland. Average monthly water consumption for households in Inland is nearly double that of Coastal, which is also likely driven by the need for more outdoor water consumption due to larger lawns. Inland also experiences significantly greater evapotranspiration than Coastal, further driving larger water consumption needs. Finally, the Coastal service area is wealthier, as indicated by higher average property values.

## 4 Empirical Framework

We first estimate causal price elasticities induced by the drought surcharges adopted within nonlinear BBRs. There are two primary challenges to identifying casual effects. First, utilities often implement many non-price water conversation programs during droughts at the same time as price changes. During the California drought of 2011-2017, the state and local utilities experimented with a suite of policies to curb demand. These include the mandatory water restrictions ordered by the governor, public information campaigns, rebates for installing turfgrass, water audits, etc. Simply observing changes in water consumption before and after implementation of drought surcharges cannot identify how much of any observed water conservation can be attributed to prices alone.

The second econometric challenge is the well-known issue of simultaneity between prices and quantity that arises under nonlinear rates (Olmstead et al., 2007; Olmstead, 2009; Wichman et al., 2016). With BBRs (as well as traditional IBRs), the marginal and average price faced by the household by definition changes as a function of consumption. Failing to account for this source of endogeneity will result in ordinary least squares (OLS) demand estimates that are biased and potentially upward-sloping, since marginal and average prices rise with consumption.

We design a novel identification strategy that solves both of these econometric issues by exploiting exogenous, policy-induced changes in marginal and inframarginal prices to identify the causal effect of surcharge pricing on demand. First, we train machine learning models using data prior to the declared drought emergency to generate counterfactual out-of-sample consumption predictions for each household during the drought surcharge period. These counterfactual consumption schedules represent what household consumption would have been absent the many changes in price and non-price policies implemented during the drought emergency. We then use the counterfactuals to define a predicted price change that captures exogenous changes in relative exposure to drought surcharges. We use the predicted price change as an instrumental variable in a two-stage least squares (2SLS) demand framework to instrument for the actual marginal or average price. We first outline the procedure used to generate our counterfactual predictions. We then elucidate the construction of and intuition behind our instrument, and conclude with a discussion of our primary estimating equation.

## 4.1 Counterfactual Demand Predictions

We begin our analysis by using machine learning to generate counterfactual predictions for monthly household-level water consumption. Specifically, we use random forests to train models of household water consumption using data collected before the drought emergency was declared (Breiman, 2001). We use random forests to generate predictions in part because of their ability to capture highly complex interactions and nonlinear relationships between candidate predictor variables (Hastie et al., 2009). In Table A.1, we provide evidence that using random forests indeed does buy us additional predictive accuracy in the pre-drought surcharge pricing period over simpler OLS predictions.[8] Previous literature has also shown that random forests perform well in predictive settings where the goal is ultimately to recover causal estimates of policy impacts on demand for utility services like electricity (Prest et al., 2023).

Our training period is all months prior to January 2014, when the first drought emergency was declared. While drought conditions had already started to worsen and some drought-related

[8] In Appendix C, we provide results from a series of diagnostic exercises to ensure the reliability of our generated counterfactual predictions. These include comparing model errors (Figure A.2 and Table A.1), tuning several key random forest model parameters (Figure A.3), examining variable importance plots for our final predictions (Figure A.4), and generating predictions under alternative approaches (Figure A.5).

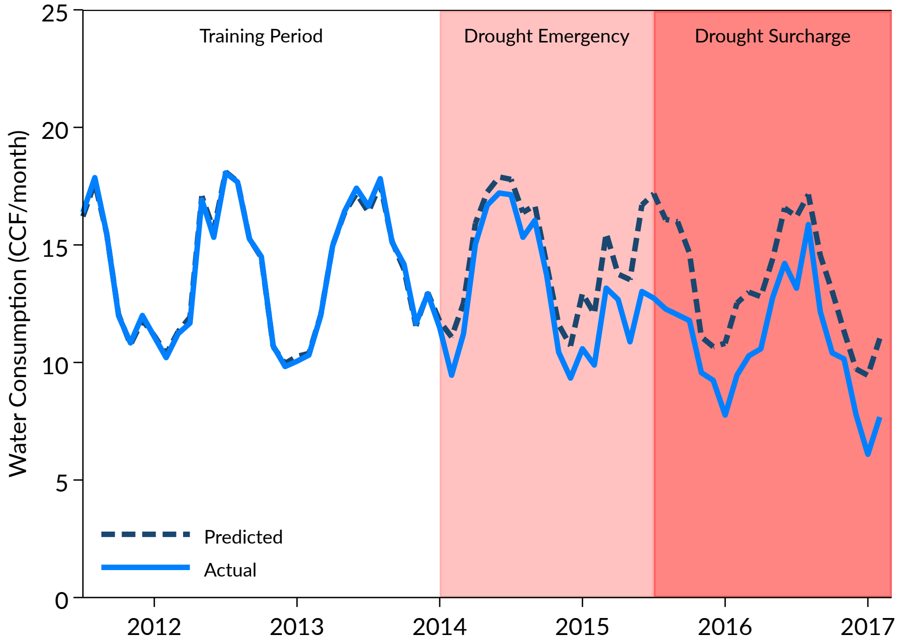
policy changes like conservation messaging were already under way during this time, we are limited by our lack of data prior to 2011 for either utility. By limiting our training period to data from 2011-2013, our predictions reflect baseline water consumption under drought but before anticipatory consumption effects related to intensive drought emergency policies began. Our approach mirrors that of Burlig et al. (2020) and Prest et al. (2023) in that we make out-of-sample predictions for years outside of the training sample in order to represent what an accurate counterfactual without any policy change would look like. We train the algorithm using a number of candidate predictor variables, including weather data, household and property characteristics, water budgets, demographic data at the census block-group level, month-of-sample dummies, and zip-code dummies. We implement the algorithm by generating 500 trees separately for each utility. We then use the resulting outputted ensemble of trees to generate out-of-sample predictions from 2014 onwards. We are particularly interested in the out-of-sample predictions from July 2015 to February 2017, when drought surcharges were in place for both the Coastal and Inland utilities.

We demonstrate our approach visually in Figure 2. The figure shows the time series for both average predicted ($\hat{q}_{it}$) and actual consumption ($q_{it}$) separately for each utility. We partition the figures into three discrete time periods: the pre-drought months used to train the random forest algorithms ("Training Period," mid-2011 to December 2013); the period in which the drought emergency had been declared but drought surcharges were not yet in effect ("Drought Emergency," January 2014 to June 2015); and the period in which drought surcharges were in effect ("Drought Surcharge," July 2015 to February 2017). As expected, during the training period the predictions perform quite well on average. After the training period, $q_{it}$ falls below $\hat{q}_{it}$ in the aggregate, which remains at a similar level to that of the training period.

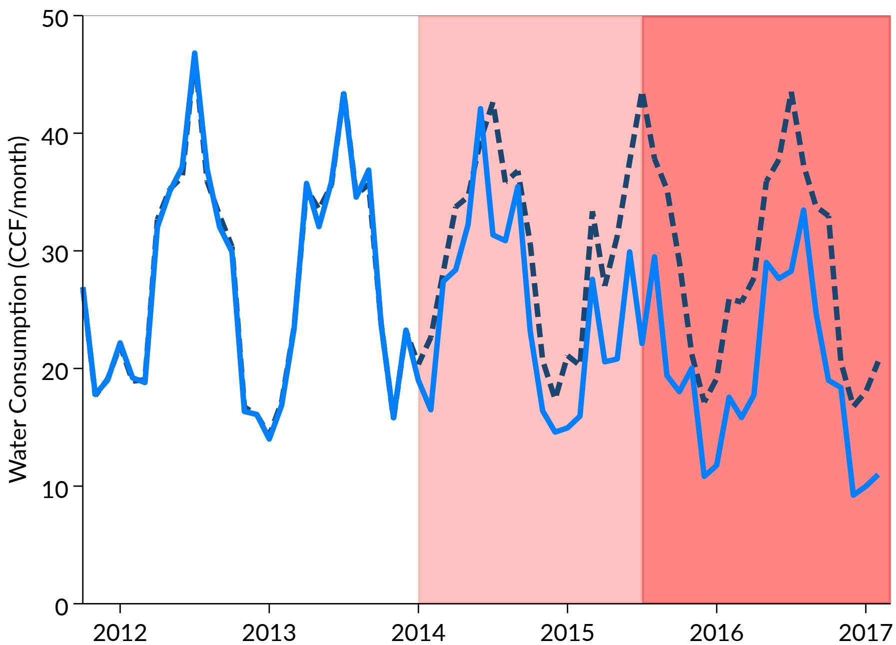
The gap in Figure 2 between $\hat{q}_{it}$ and $q_{it}$ that emerges in 2014 represents aggregate water conservation during the drought. This difference arises because the predictions, while adjusting for contemporaneous weather conditions, do not incorporate any drought-related policies enacted in 2014 and beyond. The difference can be attributed to the full suite of drought policies, including the drought surcharges. The fact that conservation occurs in the drought emergency period before price changes were implemented demonstrates that non-price conservation is present in our setting, and highlights the importance of isolating the role of prices from other drought policies.

### 4.2 Construction of Price Instrument

We next turn to addressing the endogeneity of prices and quantity, which arises in this setting due to the simultaneous determination of quantities and prices under nonlinear rates. With BBRs, the marginal price faced by a household rises with quantity consumed relative to the budget. One solution is to use a structural discrete-continuous choice framework in which a household first makes the discrete choice of which consumption block to consume in (i.e., 100-125% of budget), and conditional on that choice, a second continuous choice of how much water to consume (Hanemann, 1984; Hewitt and Hanemann, 1995; Olmstead, 2009). This solution relies on




(a) **Coastal**




(b) **Inland**

Figure 2: Predicted and Actual Consumption Over Time

**Notes:** The figure presents the time series of average actual and predicted consumption in each month-of-sample for each utility separately. The training period data used to train the random forest algorithm up to December 2013 is unshaded. The period in which the drought emergency had been declared but drought surcharges were not yet in effect is shaded in pink (January 2014 to June 2015). The period in which drought surcharges were in effect is shaded in red (July 2015–February 2017). Actual consumption (blue solid line) falling below predicted consumption (navy dashed line) indicates water conservation in the aggregate.

untenable information assumptions in the context of BBRs, as households do not know what their exact budget will be until the end of the billing period, when evapotranspiration over the billing period has been fully observed and budgets can be calculated (but consumption can no longer be altered). Therefore, households cannot *ex ante* make the discrete choice of what block to consume in. A separate reduced-form approach to demand estimation common in the prior literature uses the full schedule of marginal prices set by the utility as an instrument for marginal price in a 2SLS framework (Olmstead, 2009; Wichman et al., 2016). This solution, although exogenous to contemporaneous consumption, can be criticized for violating the exclusion restriction.

We address the simultaneity of price and quantity by exploiting predetermined differential exposure to the exogenous change in price due to drought surcharges. First, we use $\hat{q}_{it}$ and water budget formulas to generate predicted prices during the drought surcharge period. Specifically, we calculate the price the household would have faced under surcharge pricing based on the household's historical consumption patterns and prevailing weather conditions. This predicted price ($\hat{p}_{it}$) is defined by predicted consumption relative to the budget and serves as the first input into our instrument. Next, we again take $\hat{q}_{it}$ for each household-month during the drought surcharge period, but this time calculate the price the household would have paid for that level of predicted consumption before the drought emergency was declared ($\hat{p}_{it}^{pre}$). This second predicted price represents a baseline price that households regularly faced before the drought emergency was declared.

Our final instrument is the difference of these two predicted prices: $\Delta\hat{p}_{it} = \hat{p}_{it} - \hat{p}_{it}^{pre}$. Taking the difference of these two predicted prices isolates the exogenous variation in prices that is induced specifically by the policy change in rate structure. For example, households who regularly consume well under their budget faced little to no price change as a result of the imposition of drought surcharges, while households who regularly consumed in the higher consumption tiers before the drought faced large changes in inframarginal and marginal prices when surcharge pricing was implemented. The instrument is similar in spirit to other "simulated" instruments regularly used in the water and electricity demand literature (e.g., Ito, 2014; Sears, 2021), and also has the spirit of a Bartik-type shift-share instrument in that it seeks to capture differential exposure to a common price shock (Bartik, 1991; Goldsmith-Pinkham et al., 2020).

The validity of our instrument rests on several standard assumptions. The exclusion restriction is that $\Delta\hat{p}_{it}$ has no effect on water demand except through the channel of actual prices faced. Our historical predictions reflect pre-determined patterns of consumption that are uncorrelated with the exogenous introduction of drought surcharges. Additionally, the predicted price difference does not depend on the response to non-price conservation or idiosyncratic demand shocks, as all predictions were generated using training data that pre-dated drought surcharges.

Figure 3 displays a visual representation of our instrument, defined using average prices. The figure presents a binscatter that plots the mean of the two components of our instrument, $\hat{p}_{it}$ and $\hat{p}_{it}^{pre}$ across the distribution of predicted consumption relative to budget in two percentage point bins. The figure shows that the gap between these two measures (our instrument $\Delta\hat{p}_{it}$)

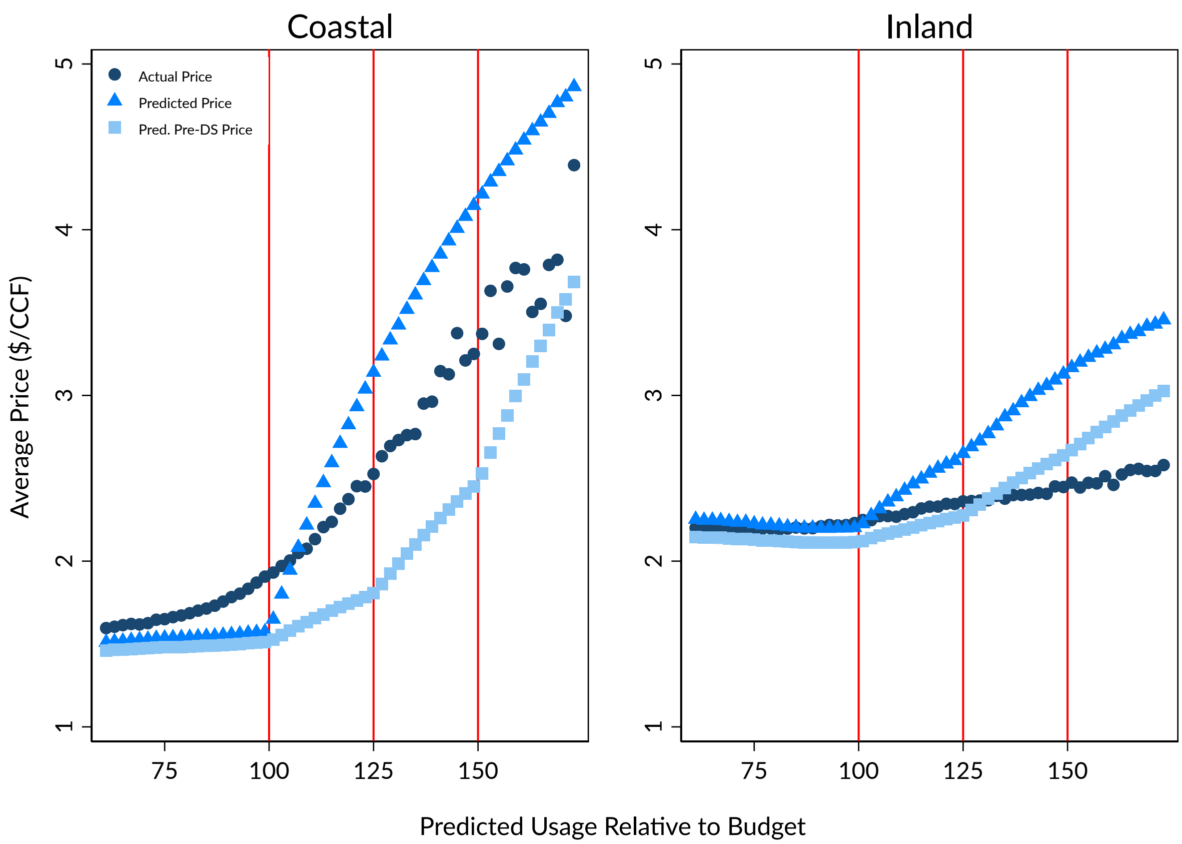



Figure 3: Relationship between Instrument and Actual Prices

**Notes:** The figure presents a binscatter that illustrates the relationship between the two components of our instrument and actual prices faced. Actual average prices faced by household-months are plotted over the distribution of predicted consumption relative to budget in a series of two percentage point bins with navy circles. Predicted prices under drought surcharge pricing are represented by blue triangles, and predicted prices using pre-drought surcharge period prices are represented by light blue squares. The difference between these two predicted price measures is our instrument, and is correlated with actual price faced. The red vertical lines represent the BBR tier thresholds.

is on average quite small whenever we predict that a customer will consume under the budget. This makes intuitive sense as prices do not rise by much for these households. $\Delta\hat{p}_{it}$ grows larger with predicted consumption relative to budget, indicating households with higher baseline consumption levels faced relatively higher exposure to drought surcharges due to their pre-existing consumption patterns. Actual average prices faced by the household-month observations in each bin are also plotted, which rise along $\Delta\hat{p}_{it}$. The figure simultaneously demonstrates that the monotonicity assumption (values for $\Delta\hat{p}_{it}$ are larger for those with larger consumption) and the first-stage assumption ($\Delta\hat{p}_{it}$ is strongly correlated with actual prices faced) hold in our setting.

### 4.3 Demand Estimation

We use our predicted price changes $\Delta\hat{p}_{it}$ as an instrument in a reduced-form demand framework to estimate causal price elasticities for drought surcharges. Our demand function takes the form:

$$\Delta q_{it} = \beta p_{it} + \delta W_{it} + \alpha_i + \tau_t + \epsilon_{it} \tag{3}$$

where $i$ indexes households and $t$ indexes billing periods (or months). $\Delta q_{it}$ is our dependent variable and represents the difference between actual consumption ($q_{it}$) and the household's month-specific baseline level of consumption from 2011-2013, before the drought emergency ($\tilde{q}_{it}$): $\Delta q_{it} = q_{it} - \tilde{q}_{it}$.[9] This difference captures the total effect of drought surcharge pricing and other non-price drought policies on consumption within a household. Price ($p_{it}$) is our endogenous explanatory variable that we instrument for with $\Delta\hat{p}_{it}$ in the first stage of the 2SLS framework. We estimate models using both average and marginal prices given the debate around what price households respond to under nonlinear rates (Nataraj and Hanemann, 2011; Ito, 2014; Wichman, 2014; Brent and Ward, 2019; Shaffer, 2020; Cook and Brent, 2021). We assume, loosely, that average price responsiveness is driven by a form of rational inattention in which households would optimize according to marginal price levels but the information costs of doing so are prohibitive (e.g., Sallee, 2014; Wichman, 2017).

We also control for $W_{it}$, a vector of contemporaneous weather variables including evapotranspiration, precipitation, and temperature (as well as their squares). As is standard in reduced-form models of demand in panel data settings, we include both household ($\alpha_i$) and billing period ($\tau_t$) fixed effects. We calculate standard errors in two primary ways: first by clustering at the household level, and second through the use of a bootstrapping procedure developed to account for errors associated with our counterfactual predictions.[10] The time period included is from July 2015 to December 2016, when the drought surcharges were in effect. We drop January and February 2017 from our primary results due to the heavy-levels of precipitation in these months,

[9] In particular, the baseline measure $\tilde{q}_{it}$ is defined as a household's month-of-year specific average over the years 2011-2013. For example, to construct $\Delta q_{it}$ for a household in August 2015, that household's consumption for the months August 2011, 2012, and 2013 is averaged together ($\tilde{q}_{it}$) and subtracted from actual consumption by that household in August 2015 ($q_{it}$).

[10] Our standard errors are complicated by the fact that our counterfactual predictions are measured with error. We provide a full exposition of our bootstrapping procedure in Appendix C.

which can cause issues with our out-of-sample predictions. The parameter of interest in Equation 3 is $\beta$, which explains how much of the overall reduction in demand captured by $\Delta q_{it}$ can be attributed to drought surcharges. We then combine our $\hat{\beta}$ estimates with observed price and consumption levels to back out implied price elasticity estimates.

# 5 Results

## 5.1 Price Elasticity Estimates

We implement the framework outlined in Section 4 to identify the causal effect of drought surcharges on water demand under BBRs. Before estimating our demand regressions, we first check for visual evidence of "bunching" in the consumption distribution to understand if households are responding to nonlinear prices by strategically consuming at kink points in the marginal price schedule (Saez, 2010; Kleven, 2016). We must check for bunching along the distribution of consumption relative to budget as opposed to consumption alone (which is standard) due to the nature of BBRs.[11] Figure A.6 presents histograms of these distributions during the drought surcharge period for the two utilities. There is no clear visual evidence of bunching at any of the kink points in the BBR schedule, which implies that average price or some other expected price measure may be the more salient price that households respond to (Ito, 2014).

We present the base results from estimating Equation 3 in Table 2. The dependent variable is $\Delta q_{it}$, so the coefficients on prices can be interpreted as a change in CCF for a dollar change in the price.[12] Columns (1)-(2) present demand regressions using average volumetric price (AP) and marginal price (MP) for Coastal, and columns (3)-(4) present corresponding regressions for Inland. We report the Kleibergen-Paap rk Wald first-stage F-statistic for each specification, which are relatively large and consistent with the intuition from Figure 3 that we have a strong first-stage (Kleibergen and Paap, 2006). Intuitively, all of the price variables generate negative effects on consumption. Bootstrapped standard errors are presented below coefficient estimates in brackets. All price coefficients are estimated with a high degree of precision.[13]

For each specification in Table 2, we present causal point-elasticity estimates and bootstrapped standard errors. These elasticity estimates are backed out using the relevant price coefficient in each specification along with average drought surcharge period consumption and prices. Our primary elasticity estimates range from -1.03 (unit elastic) to -0.22 (inelastic), and are in the gen-

[11]For example, 10 CCF may be above budget for some households and below budget for others. Theoretically then, there is no reason why bunching should occur at any single point in the consumption distribution. However, it is plausible to believe that households could bunch at the kink points of the nonlinear BBR schedule (100%, 125% and 150% of budget).

[12]We estimate all specifications separately for each utility using the "ivreghdfe" package in Stata (Correia, 2018).

[13]Table A.2 presents the same results with the original standard errors clustered by household. Our bootstrapped standard errors in Table 2 are roughly 30-50% largely than the standard errors clustered at the household level. However, the coefficients are estimated with enough precision that statistical significance under standard levels is unaffected. This result, combined with the computational time constraints associated bootstrapping, means that we move forward with presenting clustered standard errors in other results reported in this paper.

Table 2: IV Demand Regressions

| | Coastal | | Inland | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | AP | MP | AP | MP |
| Average Price | -6.49*** | | -5.57*** | |
| | [0.52] | | [2.01] | |
| Marginal Price | | -1.83*** | | -1.58*** |
| | | [0.13] | | [0.56] |
| $\epsilon$ | -1.03*** | -0.45*** | -0.61*** | -0.22*** |
| | [0.08] | [0.03] | [0.22] | [0.08] |
| Observations | 477,326 | 480,394 | 203,259 | 203,773 |
| Households | 26,995 | 27,006 | 10,840 | 10,841 |
| Household FE | Y | Y | Y | Y |
| Month-of-Sample FE | Y | Y | Y | Y |
| First-stage F-stat | 1,070 | 1,349 | 608 | 975 |

**Notes:** The table presents estimates of $\hat{\beta}$ from estimating Equation 3. The dependent variable is the difference between contemporaneous and baseline consumption, $\Delta q_{it}$. Endogenous prices are instrumented for in the first-stage using $\Delta\hat{p}_{it}$. The time period included is from July 2015 to December 2016. Columns 1 and 3 instrument for average price, while Columns 2 and 4 instrument for marginal price. All specifications include a vector of weather covariates including evapotranspiration, precipitation, temperature, and their squares. Bootstrapped standard errors calculated according to the procedure outlined in Appendix C are presented below coefficient estimates in brackets. ***: p-val < 0.01; ** p-val < 0.05; *: p-val < 0.1.

eral range of the short-run demand elasticities estimated in the recent literature (Dalhuisen et al., 2003; Olmstead, 2010; Sears, 2021). This result is notable because most studies estimate demand elasticities for *permanent* changes in prices. However, in our setting much of the variation in prices is due to *temporary* drought surcharges. Households were also well-aware that the drought surcharges were imposed in response to severe drought conditions and not intended to remain in place in the long-run. Therefore, it is unlikely that households would have made changes to their water-using capital stock due to temporary price increases.[14] Consistent with other recent analyses, we also find more elastic demand with respect to the average price compared to the marginal price, with elasticity magnitudes more than double that of marginal price across specifications (Ito, 2014; Wichman, 2014; Browne et al., 2021).

We subject our primary elasticity estimates to a battery of robustness checks. First, in Table A.3 we alter the form of $\tau_t$ to control for fixed effects at the month-of-sample by zip-code level. In Table A.4, we make an alternative assumption that households respond to one-period lagged average or marginal price as this is the price on the immediately previous bill received. Finally, in Table A.5 we estimate a standard log-log demand equation in which the coefficients themselves can be directly interpreted as elasticities. Across these robustness checks, we largely

[14]It is possible that customers might make changes to their capital stock (like turfgrass installation, dishwashers, or washing machines) due to nonprice policies like rebates or social pressures. However, those effects are not driven by exogenous changes in inframarginal prices, which we exploit through our IV approach.

estimate similar elasticities to those reported in our primary specifications from Table 2. Across specifications, we continue to note that demand is relatively more elastic with average price than with marginal price. In most robustness specifications (8 out of 12), we estimate inelastic water demand, two estimates are close to unit elastic, and two estimates indicate price-elastic demand.

### 5.2 Characterizing the Impact of Prices on Aggregate Conservation

Given our causal price elasticity estimates, we next ask: how much of the water conservation that we observe is directly attributable to the drought surcharges themselves? We answer this question through a bounding exercise that allows us to characterize the upper and lower bounds of conservation directly attributed to prices. One critique of BBRs is that the assignment of individualized water budgets shields households from facing higher prices even if they have quite large baseline water use (due to larger budgets for households with larger lawns and in drier months). Therefore, even though the drought surcharge elasticities that we estimate are similar to the extant literature, it is important for us to accurately characterize the price changes that households were actually exposed to under the drought surcharge pricing regimes.

Since both average and marginal price are endogenous in our setting, we must make assumptions about the actual price changes that households faced under drought surcharges in order to complete our bounding exercise. First, we assume that actual prices ($AP$, $MP$) are representative of the price change. This assumption likely underestimates the actual price change because households can decrease consumption due to higher prices, which in turn dampens the realized change in price. For example, a household facing the more than \$9/CCF marginal price in Coastal may reduce consumption to under the budget and see a much lower realized marginal price, which would underestimate the true price change they responded to. The second assumption we make in our bounding exercise is that predicted prices ($\widehat{AP}$, $\widehat{MP}$) are representative of the price change that households faced. This assumption likely overestimates the total price change households faced because the predictions do not account for non-price conservation.

Table A.6 presents a series of summary regressions that help to characterize these changes in prices faced by households under drought surcharge pricing. In each specification, we regress the relevant price measure ($AP$, $\widehat{AP}$, $MP$, or $\widehat{MP}$) against a dummy indicator for the drought surcharge period (as compared to the baseline training period of 2011-2013). While prices are still endogenous, these regressions operationalize the bounding assumptions described previously by capturing the change in the relevant price measure from the training period to the drought surcharge period. The "true" change in marginal price ranges from \$0.41–\$1.11 for Coastal and \$0.08–\$1.11 for Inland, while the "true" change in average prices faced is between \$0.12–\$0.13 for Coastal and \$0.04–\$0.33 for Inland.[15]

[15]We also consider changes in total bills in Table A.6. Interestingly, in both utilities total bills decrease under drought surcharges. While some of this decrease is surely attributable to the surcharges themselves, a substantial part is also likely due to non-price conservation. In fact, inelastic demand for water implies that if demand was changing only due to higher prices, then the average total bill would by definition need to increase, as the decrease in quantity consumed would not be large enough to fully offset the price increase. This decrease in total bills suggests that both

After characterizing the price bounds, we next need to estimate the total conservation achieved by the two utilities. Rather than compare consumption under surcharge pricing to earlier years, we take predicted consumption ($\hat{q}_{it}$) during the drought surcharge period as the appropriate counterfactual, as these predictions adjust for contemporaneous weather conditions and best represent what consumption would have been in the absence of drought-related policies. We additionally report average predicted consumption values and average prediction errors (defined as $q_{it} - \hat{q}_{it}$) in Table A.6. We predict that, on average, households would have consumed 13.73 CCF per month in Coastal and 30.49 CCF per month in Inland in the drought surcharge period had no drought policies been implemented. Average prediction errors, which reveal how far off actual consumption was from our predictions, are $-2.5$ CCF for Coastal and $-9.3$ for Inland. Dividing these prediction errors by the predicted consumption yields our estimates of total conservation for each utility: an 18.5% reduction in consumption for Coastal and a 30.5% reduction in consumption for Inland.[16]

We bring together our demand coefficients, price change bounds, and estimates of total conservation together in Table 3 to demonstrate demand responses directly attributable to the drought surcharges themselves. In each column, we present simulated changes in demand implied by our demand regressions by multiplying the relevant $\hat{\beta}$ estimates by the corresponding price change bounds and scaling by predicted consumption. Our results show that in Coastal, assuming average price responsiveness implies that drought surcharges induced a 5.8–6.0% reduction in consumption. Assuming marginal price responsiveness, drought surcharges induced a 5.5–14.8% reduction in demand. The analogous demand reductions for Inland are 0.8–6.0% under average price responsiveness and 0.4–5.8% under marginal price responsiveness. We also translate these demand reductions to their equivalent unit reductions (in 1000 CCF) in Table 3.

There are two primary takeaways from these results. First, under most model specifications the bounds estimated are fairly tight and imply that drought surcharges alone likely accounted for one-third or less of the total conservation we observe across the two utilities.[17] The fact that drought surcharges cannot explain most of the realized conservation gains is important to consider when designing future policy responses to curb water demand during times of drought. Our results suggest that non-price conservation policies play a relatively larger role in managing demand compared to drought surcharges, at least in the context of the BBRs considered here.

Second, we also note a differential response to drought surcharges across the two utilities. While households in both utilities have a similar demand response to drought surcharges, the

utilities, but particularly Inland, had significant non-price conservation at play.

[16]While the statewide goal was to achieve a 25% reduction in urban water consumption relative to 2013, the State Water Resources Board assigned utilities differing conservation targets according to their prior baseline consumption levels in terms of GPCD from summer 2014. These targets ranged from 4% to 36% for the highest-consuming utilities. Under this regulation, Coastal was assigned a 20% reduction target, and Inland was assigned a 32% reduction target. Our results imply that both utilities were close to achieving these targets, though our methodology differs from California's method of determining compliance.

[17]This result is implied by dividing the price conservation (%) point estimate by the total conservation (%) estimate for each specification. These estimates are in the ballpark of those reported in Browne et al. (2021), who attribute 40–44% of the total demand reduction observed in Fresno to price changes.

Table 3: Simulated Effect of Drought Surcharge Pricing on Demand

| | **Coastal** | | | |
|---|---|---|---|---|
| | AP | $\widehat{AP}$ | MP | $\widehat{MP}$ |
| Price Conservation (%) | -5.8 | -6.0 | -5.5 | -14.8 |
| | [-6.7,-4.9] | [-6.9,-5.1] | [-6.3,-4.7] | [-16.9,-12.7] |
| Price Conservation (1000 CCF) | -383.0 | -395.7 | -363.5 | -974.2 |
| | [-442.7,-323.3] | [-457.4,-334.0] | [-414.9,-312.1] | [-1111.9,-836.5] |
| (1) Demand Coefficient | -6.49 | -6.49 | -1.83 | -1.83 |
| (2) Price Increase | 0.12 | 0.13 | 0.41 | 1.11 |
| (3) Mean Pred. CCF, Cons. Pricing | 13.73 | 13.73 | 13.73 | 13.73 |
| (4) Mean Pred. Error, Cons. Pricing | -2.53 | -2.53 | -2.53 | -2.53 |
| (5) Total Conservation (%) | -18.45 | -18.45 | -18.45 | -18.45 |
| (6) Total Conservation (1000 CCF) | -1216.79 | -1216.79 | -1216.79 | -1216.79 |

| | **Inland** | | | |
|---|---|---|---|---|
| | AP | $\widehat{AP}$ | MP | $\widehat{MP}$ |
| Price Conservation (%) | -0.8 | -6.0 | -0.4 | -5.8 |
| | [-1.3,-0.2] | [-10.2,-1.7] | [-0.7,-0.1] | [-9.8,-1.8] |
| Price Conservation (1000 CCF) | -47.5 | -371.9 | -26.4 | -359.4 |
| | [-81.2,-13.9] | [-635.1,-108.7] | [-44.8,-8.1] | [-609.3,-109.4] |
| (1) Demand Coefficient | -5.57 | -5.57 | -1.58 | -1.58 |
| (2) Price Increase | 0.04 | 0.33 | 0.08 | 1.11 |
| (3) Mean Pred. CCF, Cons. Pricing | 30.49 | 30.49 | 30.49 | 30.49 |
| (4) Mean Pred. Error, Cons. Pricing | -9.30 | -9.30 | -9.30 | -9.30 |
| (5) Total Conservation (%) | -30.49 | -30.49 | -30.49 | -30.49 |
| (6) Total Conservation (1000 CCF) | -1894.79 | -1894.79 | -1894.79 | -1894.79 |

**Notes:** The table presents estimates of water conservation directly attributable to drought surcharges in both percentage change (%) terms and in 1000 CCF. These estimates are constructed as nonlinear combinations of demand coefficients and prediction errors from our demand models in Table 2. 95% confidence intervals are presented below point estimates in brackets. Relevant parameters underlying point estimates are presented below point estimates for each utility. Demand coefficients are sourced from Table 2. Price increases are sourced from Table A.6. For back-of-the-envelope verification, multiplying (1) $\times \frac{(2)}{(3)}$ yields the price conservation point estimate in %. Dividing (4) by (3) yields (5), the total conservation estimate in %. Dividing the price conservation % point estimate by (5) and multiplying by (6) yields the price conservation point estimate in 1000 CCF.

aggregate effect is relatively smaller in Inland. This is partly due to a much larger non-price demand response: total conservation was much larger in Inland in both absolute and percentage terms. However, the nature of BBRs also affected the efficacy of drought surcharges. Surcharge pricing only increased prices for households consuming above their allocated budget. Since Inland households on average have larger lot sizes and therefore larger budgets, they are less likely to consume above their budget and actually face higher drought surcharge prices. Households engaging in non-price conservation are even less likely to consume above their budget. This is seen in the small price changes that households actually observed. In Inland, average and marginal prices only increased by \$0.04 and \$0.08 respectively, and average bills actually decreased during the drought surcharge period.

To further illustrate the point that price signals are potentially dampened under BBRs, in Table 4, we present a series of descriptive regressions in which we assess the differential conservation responses of heterogenous user classes under drought surcharge pricing. We begin by defining user classes based on average pre-drought surcharge pricing period consumption, budgets, irrigable area, and property values. We define two categories for each: whether a household was above or below the median in the pre-period. The primary outcome of interest is a dummy variable for whether a household reduced their consumption relative to budget between the training period of 2011-2013 and the drought surcharge period. The regressor of interest is a dummy for whether a household was in the above median category based on pre-period characteristics. As a result, the coefficients can be interpreted as a change in the probability of exhibiting conservation associated with being a "large" consumption/budget/irrigable area or high property value household.

Table 4: Probability of Exhibiting Conservation by User Classes

| | Consumption | | Budget | | Irrigable Area | | Property Value | |
|---|---|---|---|---|---|---|---|---|
| | (1) Coastal | (2) Inland | (3) Coastal | (4) Inland | (5) Coastal | (6) Inland | (7) Coastal | (8) Inland |
| **1**[Above Median] | 0.08*** | 0.12*** | -0.02*** | -0.15*** | -0.04*** | -0.08*** | -0.02*** | -0.02** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Observations | 27,006 | 10,841 | 27,006 | 10,841 | 27,006 | 10,841 | 27,006 | 10,841 |
| P(Conserve ∣ Below Median) | 0.60 | 0.67 | 0.65 | 0.81 | 0.65 | 0.77 | 0.65 | 0.74 |
| P(Conserve ∣ Above Median) | 0.68 | 0.78 | 0.63 | 0.64 | 0.63 | 0.67 | 0.63 | 0.71 |

**Notes:** The table presents a series of household-level regressions that estimate the proportion of households that reduced consumption relative to budget relative to the training period of 2011-2013. The dependent variable is a dummy for whether a household's average consumption relative to budget was lower under drought surcharge pricing. The primary regressor of interest is a dummy variable for whether the household was above the median level for two different user classes: consumption and water budgets. These classes are defined on pre-drought surcharge pricing data. All specifications include a vector of weather covariates including evapotranspiration, precipitation, temperature, and their squares. Robust standard errors are presented below coefficient estimates in parentheses. ***: p-val < 0.01; **: p-val < 0.05; *: p-val < 0.1.

The results in Table 4 are stark. In Columns (1)-(2), the probability of conserving associated with being a large user rises by 8% in Coastal and by 12% in Inland. This suggests that drought surcharges achieved some success at inducing conservation by heavy users, with the caveat that these regressions do not separately identify price and non-price conservation. However, Columns (3)-(8) tell a more nuanced story. Being a large-budget household reduces the probability of conserving by 2% in Coastal and 15% in Inland. Similarly, having a large lawn also reduces the probability of conservation, by 4% in Coastal and 8% in Inland. Finally, in both utilities being an above median property value household reduces the probability of conservation by 2%. These results suggest that households with smaller lawns and smaller water budgets bear disproportionate shares of the conservation observed. The household-specific nature of BBRs shields some heavier users from facing higher prices, as budgets increase with irrigable square area. As a result, the conservation signal sent by drought surcharges is weakened.

These two results have important lessons for how utilities use drought surcharges moving forward. If the goal is to use drought surcharges on their own to send an appropriate price signal reflecting water's relative scarcity, those price changes must bind for a significant portion of households or the scarcity signal will be weakened. However, when surcharges are paired with a suite of other non-price conservation policies, as they were in both Coastal and Inland during this time period, non-price conservation efforts may play a more important role in managing demand, with drought surcharges targeting only those households whose demand has been impervious to prior non-price conservation efforts.

# 6 Distributional Analysis

We now turn our focus towards the distributional implications of the drought surcharges layered within BBRs that we observe here. When faced with the state-mandated cuts, many utilities chose to implement price increases, whether through surcharges, conservation pricing, or fines (as in Pratt (2023) and Browne et al. (2023)). This is likely to become more common since surcharge pricing does not require the same regulatory scrutiny as general rate setting since it pays for temporary demand-side management efforts during droughts. Our demand estimates reveal that, in the aggregate, households responded to *temporary* drought surcharges largely in the way that they would have responded to permanent changes in rate structure. Inelastic demand for an essential good (residential water) with no perfect substitutes implies that households are likely to bear a substantial portion of the burden of price increases. This naturally raises the question: to what extent were these price increases shared equitably across households?

## 6.1 Characterizing the Incidence of Water Expenditures

A first-order concern is understanding how observed water expenditures are shared across the income distribution. We begin with the simple exercise of calculating observed average monthly expenditures as a percentage of a household's monthly income across income groups.[18] The results, presented in Figure A.7, show that the rates we observe, like most utility expenditures, are regressive: lower-income households devote a larger share of their income to water expenditures under the existing rates, both before and after the introduction of surcharge pricing. The overall regressive nature of the rates observed here is not specific to BBRs. It is well-understood that water rates in general are a regressive means of raising revenues as opposed to other mechanisms such as income or property taxes that more directly target wealth (Cardoso and Wichman, 2022).

The addition of drought surcharges on top of BBRs adds an additional layer of complexity to understanding distributional effects. Although surcharges are designed with conservation as the primary goal (as opposed to equity), surcharges could reduce the regressivity of BBRs if high-income, high-use households face price increases. However, it is difficult to draw any such conclusions about changes in regressivity of surcharges from Figure A.7 because of the presence of non-price conservation that occurs between the pre-surcharge pricing period and the period

[18]We do not directly observe household income in our data. To estimate household income, we implement an approach that combines property value data with Census data on average household incomes in each block group. Our procedure ranks households within each block group by their observed property value and then assigns each household an estimated income based on the observed income distribution reported in the Census data for that block group. We describe this procedure fully in Appendix D.

in which surcharges were implemented. To assess whether drought surcharges improve the redistributive properties of BBRs, we leverage our counterfactual predictions during the drought surcharge pricing period from the demand analysis, $\hat{q}_{it}$. We calculate water bills using $\hat{q}_{it}$ under the BBRs with surcharges, as well as using prices from before the introduction of surcharge pricing. Using $\hat{q}_{it}$ to calculate counterfactual bills is useful because the predictions represent a baseline level of consumption for each household that is unaffected by the full suite of drought policies in place during the surcharge pricing period. This allows us to isloate changes in expenditures that result from the introduction of drought surcharges.

We illustrate the distribution of predicted expenditures both before and during surcharge pricing by constructing a series of Lorenz curves and Gini coefficients similar to Levinson and Silva (2022). Under the standard approach to constructing Lorenz curves, one plots the share of income held by each percentile of households, ordered by income. Lorenz curves further away from the 45-degree diagonal indicate higher levels of income equality (i.e. the poorest 50% of households may only hold 20% of aggregate income). Gini coefficients on a scale of 0 to 1 can then be calculated to indicate the relative level of income inequality. We first plot the share of predicted water bills paid by each percentile of households ordered by income, both before and during surcharge pricing. Plotting expenditures instead of income implies that a lower-hanging Lorenz curve signals more inequality in water expenditures across the income distribution. We additionally construct standard income-based Lorenz curves and Gini coefficients for comparison. By comparing the two sets of curves, we can assess the relative progressivity of the rate structures we observe. If the share of water expenditures is more equal than the share of income across the income distribution (i.e., the water expenditure Lorenz curve is closer to the 45-degree line than the income Lorenz curve), then water bills are regressive since lower income households pay a higher share of water expenditure relative to their share of income.

Figure 4 illustrates our water expenditure Lorenz curves under drought surcharges for each utility. The predicted water expenditure Lorenz curves under surcharge pricing fall slightly below the diagonal in each utility, signaling that lower-income households do bear a proportionally lower share of total water expenditures. The Gini coefficients associated with these Lorenz curves are 0.11 and 0.07 for Coastal and Inland, respectively. Figure 4 also displays the expenditure Lorenz curves that are calculated under pre-drought surcharge pricing, or standard BBRs. The Gini coefficients associated with these Lorenz curves are 0.08 and 0.07 for Coastal and Inland, respectively. In both utilities, the expenditure Lorenz curves lie nearly on top of each other, with surcharges inducing some limited increases in progressivity in Coastal.[19] We compare these results to the standard income Lorenz curves which are also plotted on Figure 4 with the blue solid line. The income Lorenz curves fall further below the diagonal than the expenditure Lorenz curves, with associated Gini coefficients of 0.32 for each utility.[20]

[19]Note that these Gini coefficients are not directly comparable to the "electric" Ginis reported in Levinson and Silva (2022), as we calculate Ginis based on the income distribution rather than the consumption distribution. This allows us to focus on how surcharges potentially redistribute income between relatively richer and poorer households.

[20]Estimated Gini coefficients for the entire U.S. are on the order of 0.4-0.42. This indicates that estimated incomes

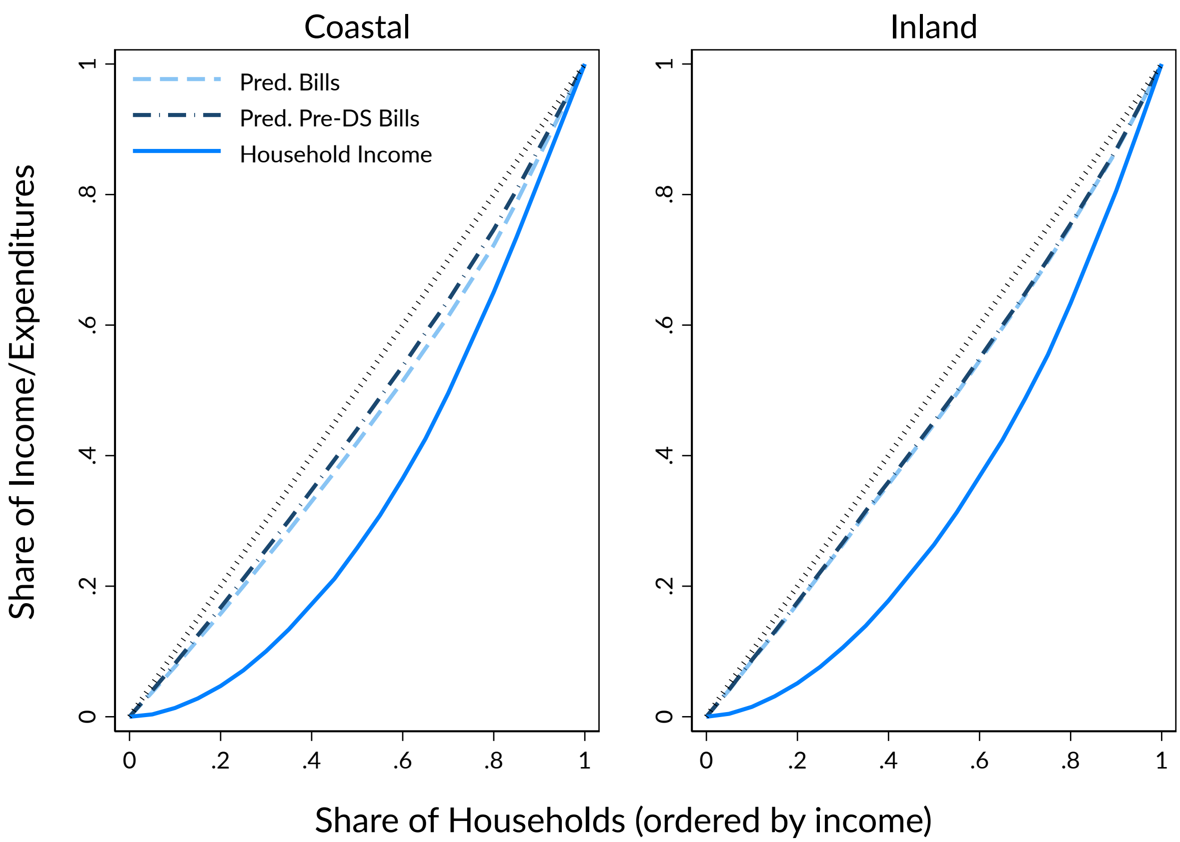



Figure 4: Distribution of Water Expenditures and Household Income

**Notes:** The figure presents Lorenz curves indicating the share of predicted water expenditures under surcharge pricing (dashed light blue line), the share of predicted water expenditures under pre-surcharge pricing (dashed navy line), and share of household income (solid blue line) that accrue to each percentile of the household distribution ordered by income. The time period included is the drought surcharge period (July 2015 - December 2016). The 45° diagonal is plotted in the dotted black line and represents perfect equality (i.e., the bottom x% of households pay x% of water expenditures).

Two key takeaways emerge. First, the regressivity documented in Figure A.7 is further confirmed by the Lorenz curves in Figure 4. This regressivity is implied by the fact that the share of total water expenditures faced by lower income households is higher than the share of total wealth held at each point along the income distribution. For example, in Coastal the bottom 50% of households in terms of income hold only 25% of aggregate income, but cover 42% of total water expenditures. In Inland, the poorest 50% of households also hold only 26% of aggregate income but pay 45% of total water expenditures. For water rates to be progressive, rates would need to be more unequal than the income distribution. Overall, the rates observed here do not lead households to pay for water in proportion to their wealth. While water utilities generally want to have progressive rate structures, their ultimate equity objectives are often not made explicit. Without knowing a utility's underlying objective function, it is difficult to say whether BBRs are achieving their equity objectives.

Second, the drought surcharges themselves do not appear to increase progressivity relative to the prices charged before the introduction of surcharges, as evidenced by the similarity of the Gini coefficients and expenditure Lorenz curves under both sets of prices. While surcharges are not designed with equity as the primary goal, significant income shifts could occur if richer, higher-use households face binding price increases. We observe little to no change in progressivity due to surcharges, despite using predicted consumption that captures pre-drought baseline consumption and does not allow for households to engage in price- or non-price conservation in response to changing conditions. This result implies that, even under optimistic assumptions, surcharges should not be expected to be much more progressive than prevailing water rates, as they do not appear to bind for enough, or the right type of, households.[21]

Finally, we unpack the distributional effects of drought surcharges by documenting how water expenditures are distributed across heterogeneous user groups, in particular the largest users that surcharges are intended to target. In Table 5 we calculate shares of total expenditures and consumption that are borne by those who go above their water budgets on average, and those in the top quartile of the budget and irrigable area distributions, all defined using the pre-drought surcharge pricing period. We find that the share of total revenues and consumption by these large user groups remains largely unchanged between the pre-drought surcharge pricing period and under surcharge pricing. The fact that shares of consumption remain largely the same across periods shows that BBRs failed to induce these large use/budget/lawn households to reduce consumption at proportionally higher rates than small use/budget/lawn households. These results along with the Lorenz curve analyses indicate that the observed BBRs failed to induce large changes in income redistribution, and that lower-consumption and lower-income households bore just as much, if not more of the burden of drought surcharges as larger-consumption and

in our two utilities are slightly more equal than in the country as a whole. Source: `https://fred.stlouisfed.org/series/SIPOVGINIUSA`. Last accessed: May 20, 2024.

[21] Another explanation is that the correlation between income and water consumption is too weak for any rate structure to be meaningfully progressive. The correlation coefficient between consumption and household income is 0.31 in Coastal and 0.24 in Inland.

Table 5: Shares of Total Revenue and Consumption Borne by Large Users

| | Pre-Surcharge Pricing | Surcharge Pricing | Difference |
|---|---|---|---|
| | | **Coastal** | |
| Over-Budget Households | | | |
| Share Total Revenue | 0.38 | 0.38 | -0.01 |
| Share Total CCF | 0.30 | 0.29 | -0.02 |
| Heavy-Use Households | | | |
| Share Total Revenue | 0.51 | 0.51 | -0.00 |
| Share Total CCF | 0.45 | 0.44 | -0.01 |
| Large-Lawn Households | | | |
| Share Total Revenue | 0.39 | 0.40 | 0.01 |
| Share Total CCF | 0.39 | 0.39 | 0.00 |
| | | **Inland** | |
| Over-Budget Households | | | |
| Share Total Revenue | 0.50 | 0.47 | -0.03 |
| Share Total CCF | 0.46 | 0.44 | -0.02 |
| Heavy-Use Households | | | |
| Share Total Revenue | 0.47 | 0.46 | -0.01 |
| Share Total CCF | 0.46 | 0.44 | -0.02 |
| Large-Lawn Households | | | |
| Share Total Revenue | 0.35 | 0.36 | 0.01 |
| Share Total CCF | 0.37 | 0.37 | 0.01 |

**Notes:** The table presents the shares of total revenue and total consumption that are generated by three separate user classes. Over-budget households are those that go over their budget on average across all months in the pre-drought surcharge pricing training period of 2011-2013. Heavy-use and large-lawn households are those in the top quartile of the distribution for these variables during the same pre-period, respectively. The third column presents differences in proportions between the two periods. We define total revenue as aggregate revenues raised from variable commodity charges specifically, and leave out fixed service fees in these calculations.

higher-income households. These results are consistent with others found in the literature, including Yoo et al. (2014) who find that lower-income and lower-consumption households users are more responsive to prices.[22] These results are also consistent with our demand analysis in that the assignment of household-specific water budgets shields some heavier users from facing the surcharges by allowing them to consume more water at lower marginal prices. Ultimately, drought surcharges must bind if they are to induce disproportionate consumption reductions by the largest users.

[22]Wichman et al. (2016) also find that low-income households are more sensitive to price increases, but they find that large users are more responsive to non-price conservation policies. El-Khattabi et al. (2021), however, find that high-users are more responsive to price, and price elasticities do not vary across the income distribution. So, the existing evidence is mixed.

### 6.2 Counterfactual Rate Analysis

While the analysis so far illustrates the equity properties of drought surcharges under BBRs, we next seek to answer: how do the rates we observe here perform along equity dimensions relative to feasible alternatives? To facilitate this analysis, we construct counterfactual rate structures for comparison with the bills households face under the existing BBRs, focusing on the surcharge pricing period. We again leverage $\hat{q}_{it}$, our measure of predicted consumption, to calculate bills under the various alternatives. As with the Lorenz curve analysis, using the predictions to calculate counterfactual bills is useful because they represent a baseline level of consumption for each household that is unaffected by concurrent drought policies. This allows us to focus on changes in bills due to variation in the alternative rate structures themselves, and not due to other non-price conservation. So as to facilitate direct comparisons between the rate structures we assume revenue-neutrality where the aggregate variable commodity charge revenues raised by the utility must remain constant across rate structures.

In particular, we construct counterfactual bills under three alternative rate structures: a uniform rate, a uniform rate coupled with a variable fixed fee tied to household income (Burger et al., 2020; Borenstein et al., 2021), and an IBR designed to mimic the tiers of the existing BBRs. Appendix D contains a full description of how we generate counterfactual bills under each of these alternative rate structures. We define bills here as the sum of commodity charges for water and the fixed service changes, and abstract away from other fees like sewer charges.

In Figure 5, we illustrate how each of the three alternative rate structures works in theory. Under uniform rates, households pay both a flat fixed fee and marginal price that are constant across all units of consumption. In the second panel, we graph rates against income to illustrate how pairing the uniform rate with a progressive fixed charge operates. As before, the marginal price is constant and therefore does not vary with income. The progressive fixed fee, however, does rise with income. We illustrate this rise in Figure 5 as a series of discrete tiers, but in theory utilities could design such a fee in a number of ways, including as a continuous measure. We return to depicting consumption on the horizontal axis in the third panel depicting a hypothetical IBR. As before, the fixed fee does not vary with consumption, but the marginal price increases in discrete tiers as users move into higher consumption tiers. Recall that these tiers are defined for all households and are not individualized as under BBRs.

We construct our counterfactual bills using predicted consumption combined with our revenue-neutrality assumption. Table A.7 presents average bills for each rate structure, broken out by the quintiles of the property value distribution. Average bills are higher in Inland due to higher consumption overall. Bills monotonically increase along the property value distribution under all rate structures for both utilities, indicating that consumption is correlated with property values. Average bills tend to be higher for IBRs in the highest property value quintiles. When considering the range of average bills, the progressive fixed fee and the IBR provide the largest spread between the lowest and highest property value quintiles in both utilities. For the progressive service charge, this result indicates that such a charge is successful in its goal of increasing the

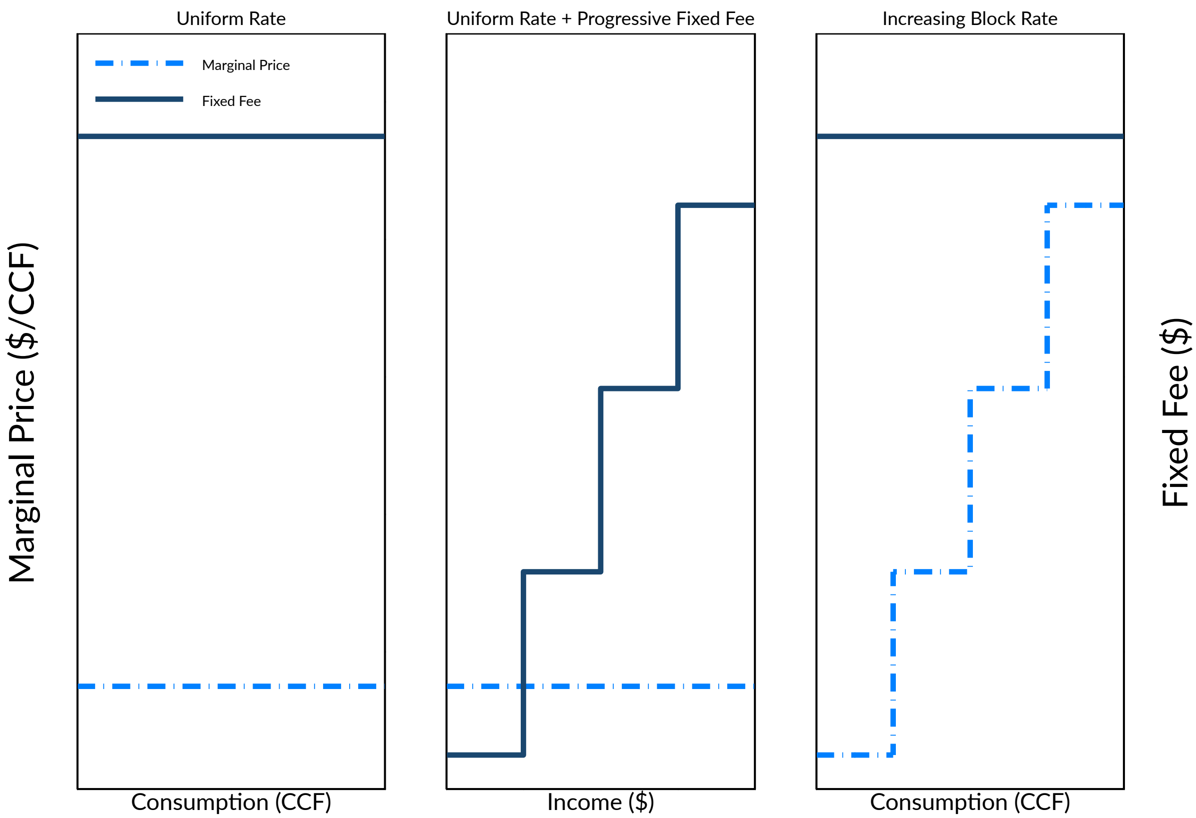



Figure 5: Counterfactual Rate Structures

**Notes:** The figure conceptually illustrates the three counterfactual rate structures we construct: a uniform rate, the same uniform rate combined with a "progressive" fixed fee tied to income, and an increasing block rate. In each panel, marginal prices are graphed on the left vertical axis, while fixed fees are graphed on the right vertical axis. The horizontal axis is consumption in CCF for the uniform rate and increasing block rate, and household income for the uniform rate + progressive fixed fee.

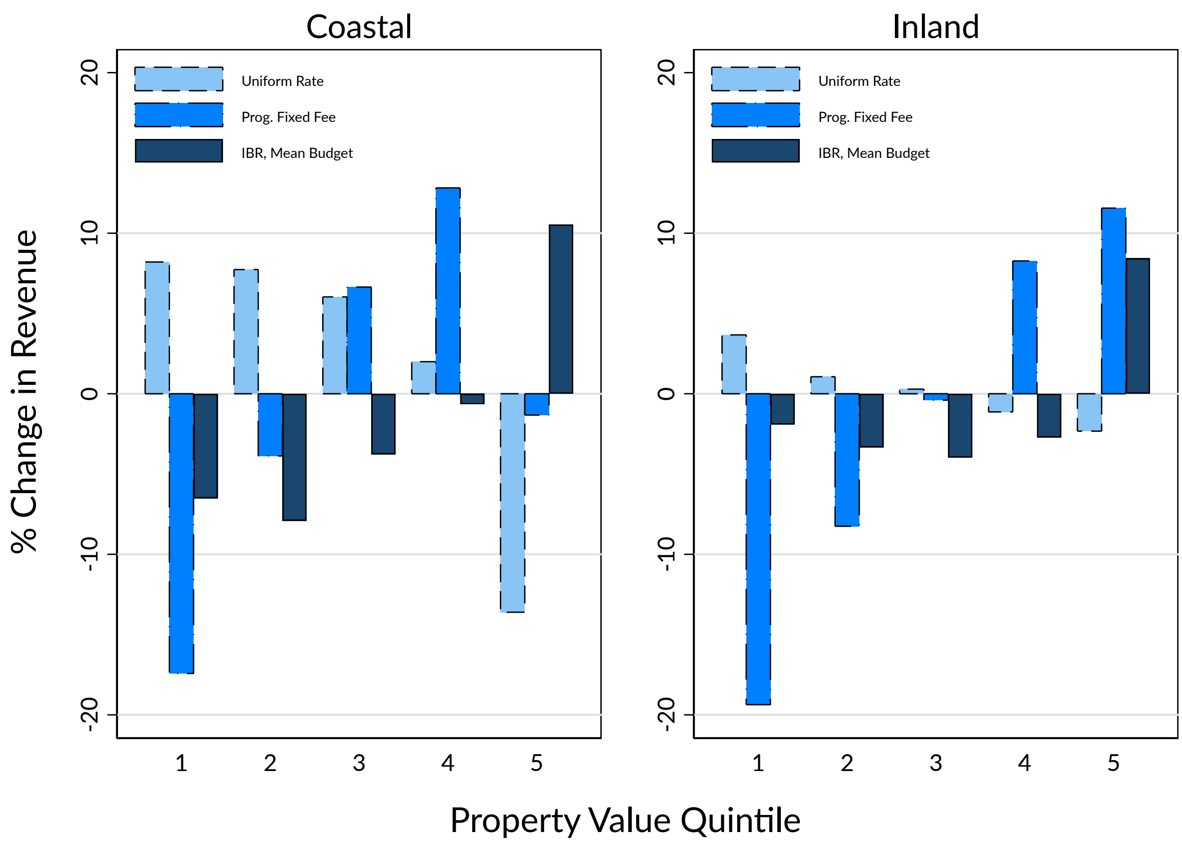



Figure 6: Total Revenue Changes by Property Value Quintiles

**Notes:** The figure presents changes in total revenues raised from each quintile of the property value distribution when moving from BBRs to each of three alternative rate structures, respectively. Negative values indicate that less revenue is raised from that quintile of homes under the alternative structure compared to a BBR, while positive values indicate that more revenue is raised from that quintile relative to BBRs.

progressivity of water expenditures. For IBRs, this result indicates that high-consuming users in more valuable homes face higher marginal prices on more units of consumption than they did under BBRs.

Focusing on average bills alone can mask important heterogeneity in how each rate structure redistributes revenue. In Figure 6, we calculate the percentage change in total bill revenues raised from each quintile of the property value distribution as a result of switching from BBRs to each of three alternatives. Figure 6 shows that in Coastal a uniform rate would shift the burden towards less wealthy households, but in Inland the uniform rate performs quite similarly to the existing BBRs. redistributing income through the fixed fee appears to be quite effective in these simulations, as evidenced by the fact that significantly lower revenues are raised from the bottom two property value quintiles in both utilities. In both utilities, the IBR structure shifts much of the burden of revenue-raising onto households in the highest property value quintile.[23]

### 6.3 Discussion

Our distributional analysis raises several points about the equity properties of the nonlinear rates we analyze here. First, BBRs appear more progressive than uniform rates only in certain settings. If a utility does not care about addressing equity through the rate structure directly, then it might be preferable to price water using uniform rates, which avoid complexities with nonlinear rates that are difficult to communicate to households (Kahn and Wolak, 2013; Brent and Ward, 2019; Shaffer, 2020). Such rates also require much less information to be collected by the utility about household size, lot size, and other factors that go into calculating water budgets. However, BBRs do have one distinct equity advantage over uniform rates in that lower-consumption tiers can be subsidized using local tax revenues and other fees. Both utilities we study here subsidize consumption in the first two tiers by using revenues from property taxes to lower marginal prices below the cost of supplying water in those tiers. Using property tax revenues driven by wealthier homes to lower water costs for the entire service area improves the progressivity of BBRs relative to uniform rates. That said, subsidizing volumetric rates for water use is known to generate allocative inefficiencies by setting incorrect incentives for consumption, particularly when lump-sum transfers can be used to redistribute costs (Levinson and Silva, 2022).

If a utility does seek to incorporate equity concerns into the rate structure, redistributing income through the fixed service charge can result in a relatively more progressive distribution of bills with far lower information costs for the utility. By combining a single marginal price that reflects the cost of supply with an income-varying service charge, such rates embed attractive efficiency and equity properties (Burger et al., 2020; Levinson and Silva, 2022). However, political constraints may make individualized service charges directly tied to income difficult to implement in practice, as evidenced by California's current efforts to implement such charges for electricity.[24] If such rates are politically infeasible, IBRs present another option to utilities. Our results suggest IBRs can achieve progressivity gains relative to BBRs, and utilities could potentially also subsidize consumption in the lower tiers with property taxes in the same way that they

[23] We enforce revenue-neutrality on these counterfactual rate structures in order to facilitate direct comparisons such as those made in Figure 6. However, this implicitly assumes that households are not able to adjust their consumption in response to changing prices when shifting from the BBR to alternative rates. Figure A.8 presents the same revenue changes by property value quintiles under an alternative scenario where we assume that households can shift consumption one time in response to changing prices, with a price elasticity of demand equal to -0.5. This allows for the more realistic scenario of consumption responding to prices, with the tradeoff that all scenarios now are not revenue-neutral. The results are largely similar to those in Figure 6. One change is that IBRs do not hit the highest property-value quintiles as hard. These high-use households are able to adjust consumption downwards in response to facing higher prices sooner than they do under BBRs.

[24] The California Public Utilities Commission is currently moving forward with efforts to implement an income-based fixed fee for electricity consumption, first proposed by Borenstein et al. (2021) and subsequently mandated by law in 2022. These efforts have generated significant political backlash and face potential repeal efforts. Sources: `https://www.utilitydive.com/news/california-lawmakers-backpedal-on-income-based-utility-charges-as-ious-oth/707859/`. & `https://energyathaas.wordpress.com/2024/05/13/reality-checking-californias-income-graduated-fixed-charge/`. Last accessed: May 15, 2024.

currently do with BBRs.

As mentioned previously, Proposition 218 presents another legal constraint on the ability of utilities to incorporate equity concerns into the rate-making process. The restrictions that Proposition 218 places on water utilities may make it exceedingly difficult to experiment with alternative rate structures once an approved rate structure has been set in place. Considering this constraint, in Appendix D we discuss a final set of counterfactual results (presented in Figure A.9 and Figure A.10) in which we assume that the utilities are restricted to keeping their BBRs intact. We then consider how tweaks to the BBR formula can induce changes in progressivity, and show that combining individualized indoor budgets with an average outdoor budget may further improve equity properties of BBRs.

Equity considerations by utilities are also different under drought than under times of relative abundance. When entering into an extended drought period, utilities must assess not only how to induce permanent conservation, but also how to temporarily curb excessive or wasteful uses of water while maintaining base levels of indoor water use. By assigning each household an individualized water budget, BBRs have the ability (unlike the other rate structures considered here) to transmit individualized information to each household about what consumption the utility would ultimately consider "wasteful". Such an approach may be a more effective option to curb excess water demand than other options such as enforcement of mandatory water rationing.[25]

Considering the sum of the evidence, the combination of drought surcharges with nonlinear BBRs possesses both positive and negative equity properties. Our analysis has noted several issues with BBRs, most notably that by tying prices to a budget, higher prices are less likely to bind for higher users with higher budgets, counteracting the purported conservation signal the utilities are intending to send. Because household income is positively correlated with the inputs to the budget formula, BBRs embed an implicit transfer from low-income households to high-income households. At the same time, the use of local property taxes to subsidize lower consumption tiers works to reverse this effect by embedding transfers from high-income to low-income households, with the net effect of these competing transfers ambiguous. Ultimately, whether the water budgets themselves effectively transmit information about scarcity and serve as a non-price conservation tool is a key question that we are unable to address directly, as we lack sufficient pre-BBR data from both utilities studied here.[26] Knowledge of the efficacy of the budgets themselves (along with knowledge of the utility's ultimate objective function when setting rates) is needed to definitively claim that BBRs are useful tools to achieve conservation and equity goals.

[25]One of the utilities in this study enforced mandatory rationing days during an earlier California drought in 2008-2009. Internal data showed no significant overall conservation due to a rebound effect where water use increased on non-rationing days, and the utility faced widespread customer backlash.

[26]Coastal used an IBR structure before switching to BBRs, while Inland previously used a uniform rate. Pérez-Urdiales and Baerenklau (2019) provide early evidence that budgets can serve as an effective information signal to high users when switching from uniform rates.

# 7 Conclusion

In this paper, we study the introduction of drought surcharges layered within nonlinear BBRs as a tool for urban water demand management. Our demand analysis indicates a largely price-inelastic response to the temporary increases in marginal and inframarginal prices. Further investigation shows that these surcharges alone cannot explain the majority of the conservation we observe. While utilities often seek to combine price and non-price conservation approaches, for drought surcharges to sufficiently signal scarcity they must bind for a significant portion of households. BBRs undercut their effectiveness by shielding high-users with large lots and lawns from ever facing higher prices. Our comparison of hypothetical rate structures suggests that BBRs do not clearly dominate other rate structures along equity dimensions, although we ultimately cannot definitively conclude that BBRs are welfare-dominated.

Climate change will continue to exacerbate water scarcity moving forward, making the need to effectively conserve water during droughts increasingly important. Our results stress the need for policymakers to consider the role that non-price policies play in inducing conservation, as surcharges alone are not enough to explain the demand response observed in the data. Whether the budgets themselves effectively serve as a non-price conservation tool is an under-studied question that future research should address. When turning to price-based policies, it is vital that they send an appropriate price signal that accurately reflects the scarcity value of water. Assigning high marginal prices, but then allocating large quantities of cheap water to households with large lawns through water budgets muddies this price signal and undercuts the effectiveness of surcharge pricing. Ultimately, utilities concerned with balancing conservation and equity concerns during drought should consider carefully how surcharges interact with existing policies like water budgets before adoption.

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# Online Appendix – Not For Publication

## A Additional Results

### A.1 Additional Figures

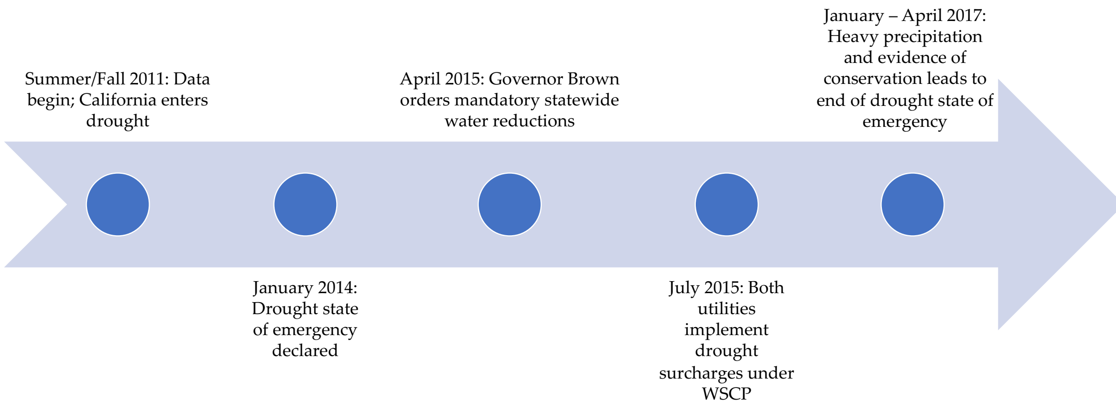
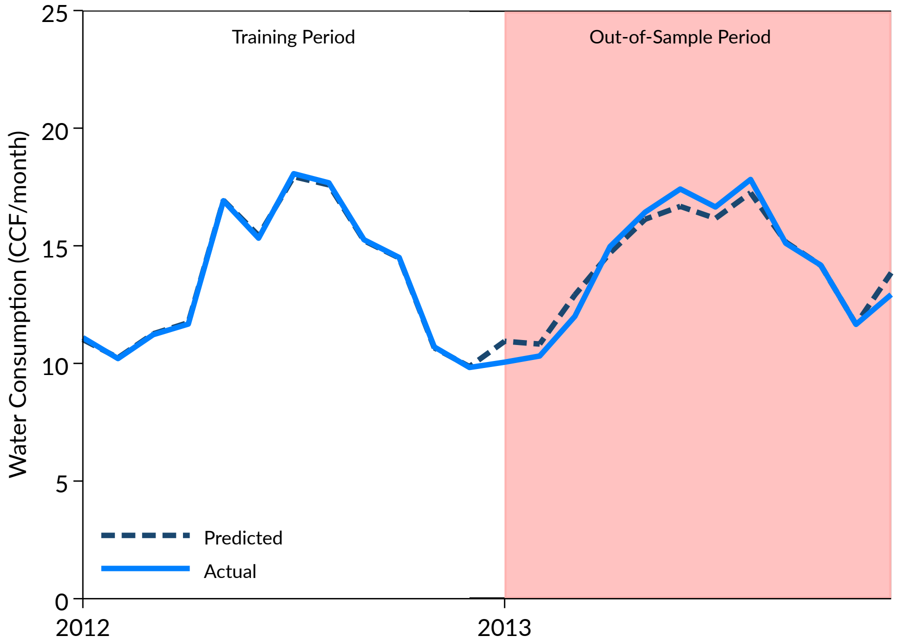
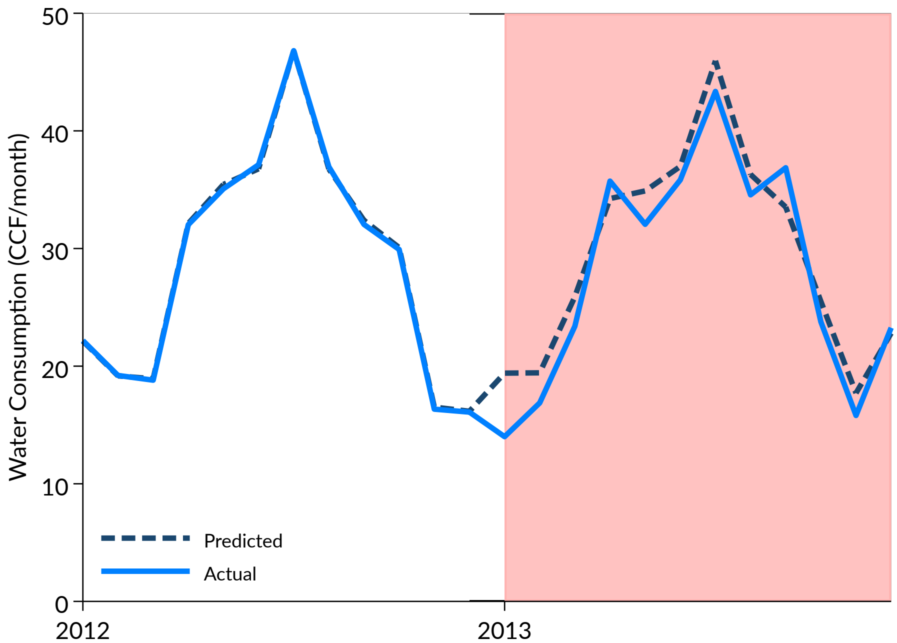



Figure A.1: Timeline of 2011-2017 California Drought

**Notes:** The figure presents a visual timeline of the important events surrounding the California drought of 2011-2017 and how they relate to the billing data used in the analysis.



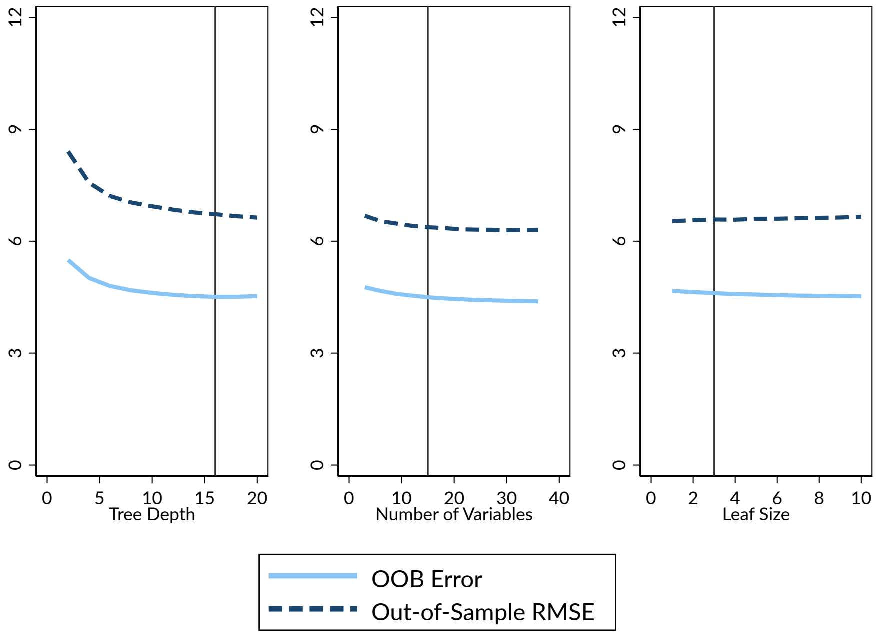

(a) **Coastal**



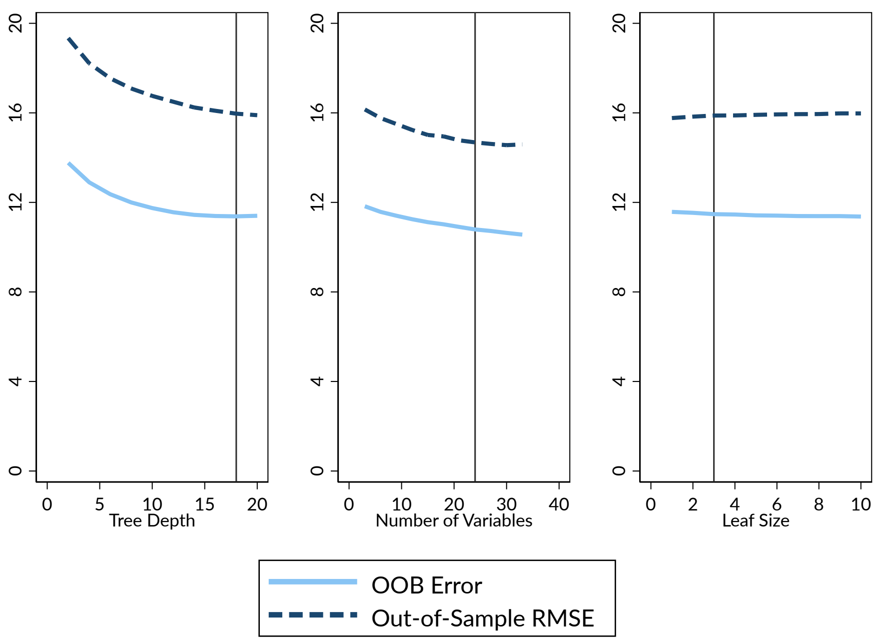

(b) **Inland**

Figure A.2: Predicted and Actual Consumption Over Time, Diagnostic Predictions

**Notes:** The figure presents the time series of average actual and predicted consumption in each month-of-sample for each utility separately, with actual consumption represented by the blue solid line and predicted consumption represented by the navy dashed line. Monthly averages are plotted for the diagnostic exercise in which we use 2012 data only to predict entirely out-of-sample in 2013.



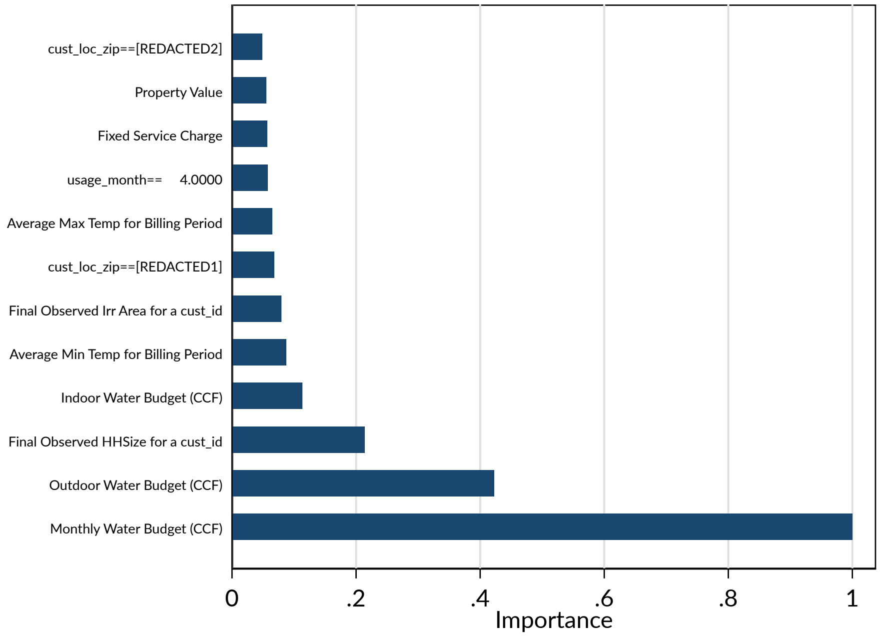

(a) **Coastal**



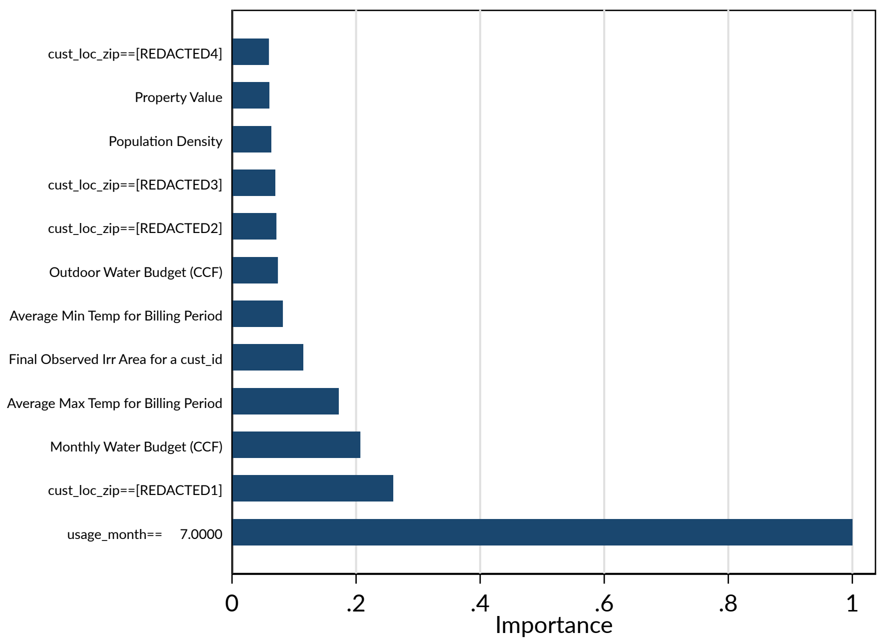

(b) **Inland**

Figure A.3: Random Forest Parameter Tuning

**Notes:** The figure presents results from our parameter tuning exercise in which we re-estimate predictions and errors over a range of discrete values. We repeat this exercise for three random forest tuning parameters, separately for each utility: tree depth, number of candidate predictor variables made available to the random forest algorithm, and minimum leaf size. Light blue solid lines plot OOB error rates, and dashed navy lines plot out-of-sample RMSE values over the range of parameter values considered. The values we choose for use in our generation of our full set of predictions are represented by the black vertical lines in each panel.



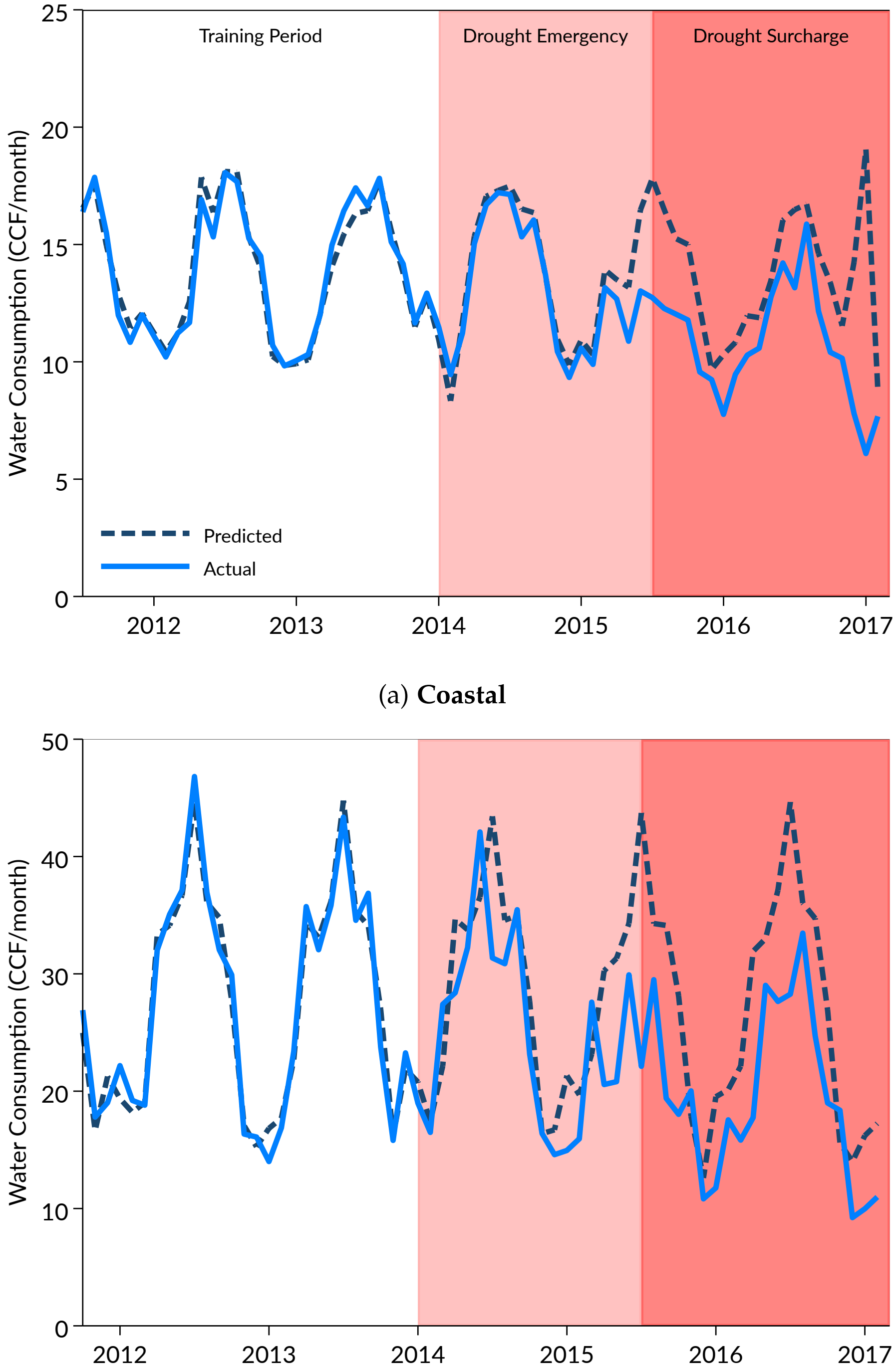

(a) **Coastal**




(b) **Inland**

Figure A.4: Random Forest Variable Importance Plots

**Notes:** The figure presents standard random forest variable importance plots for each utility separately. The top 12 most influential predictors are presented on a re-scaled measure [0, 1], with 1 being the most influential and 0 being the least influential.




(a) **Coastal**



(b) **Inland**

Figure A.5: Predicted and Actual Consumption Over Time, Panel Fixed Effect Predictions

**Notes:** The figure presents the time series of average actual and predicted consumption in each month-of-sample for each utility separately. The predictions here are generated using a panel fixed effects specification with weather covariates and household-by-month-of-sample fixed effects. The training period data used to estimate the model up to December 2013 is unshaded. The period in which the drought emergency had been declared but drought surcharges were not yet in effect is shaded in pink (January 2014 to June 2015). The period in which drought surcharges were in effect is shaded in red (July 2015 - February 2017). Actual consumption falling below predicted consumption indicates water conservation in the aggregate.

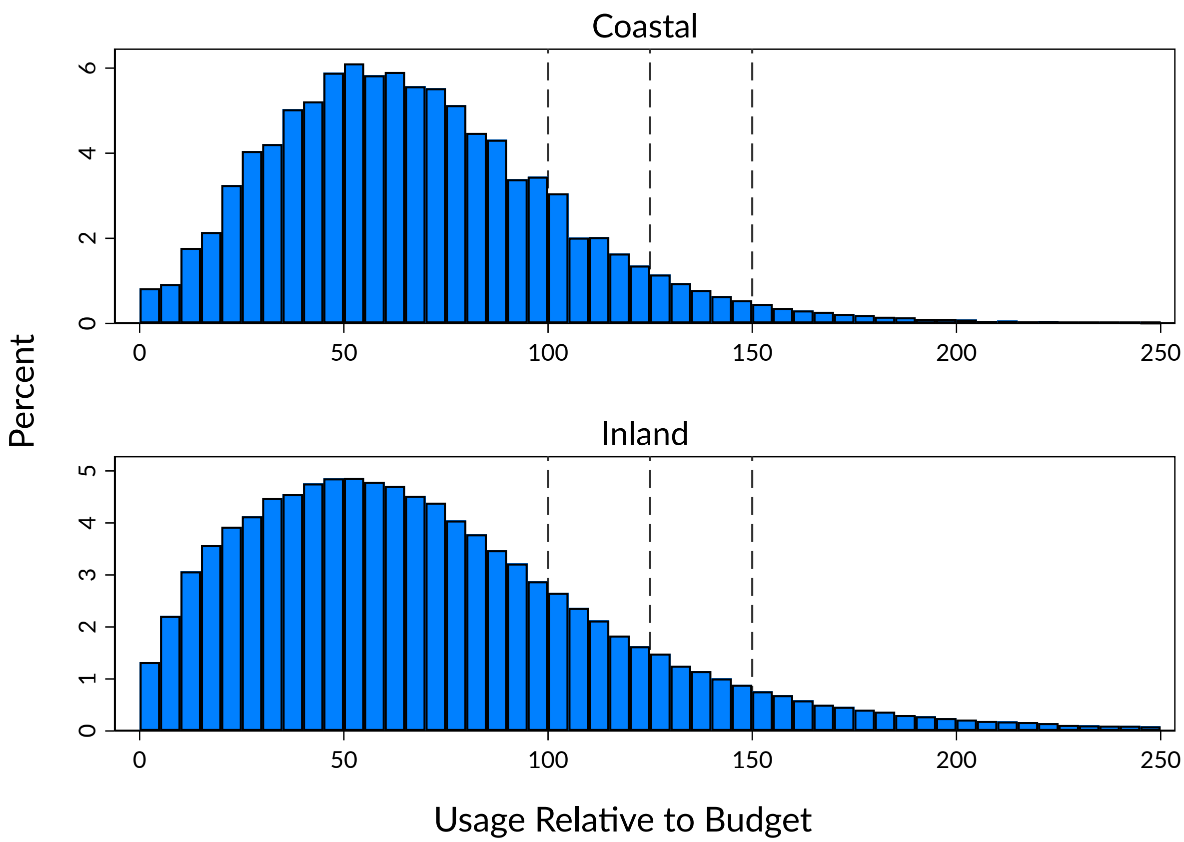



Figure A.6: Distribution of Usage Relative to Budget

**Notes:** The figure presents histograms that illustrate the distribution of usage relative to a household's water budget for household-months during the drought surcharge period. Dashed vertical lines show the relevant break points for the BBR tier thresholds.

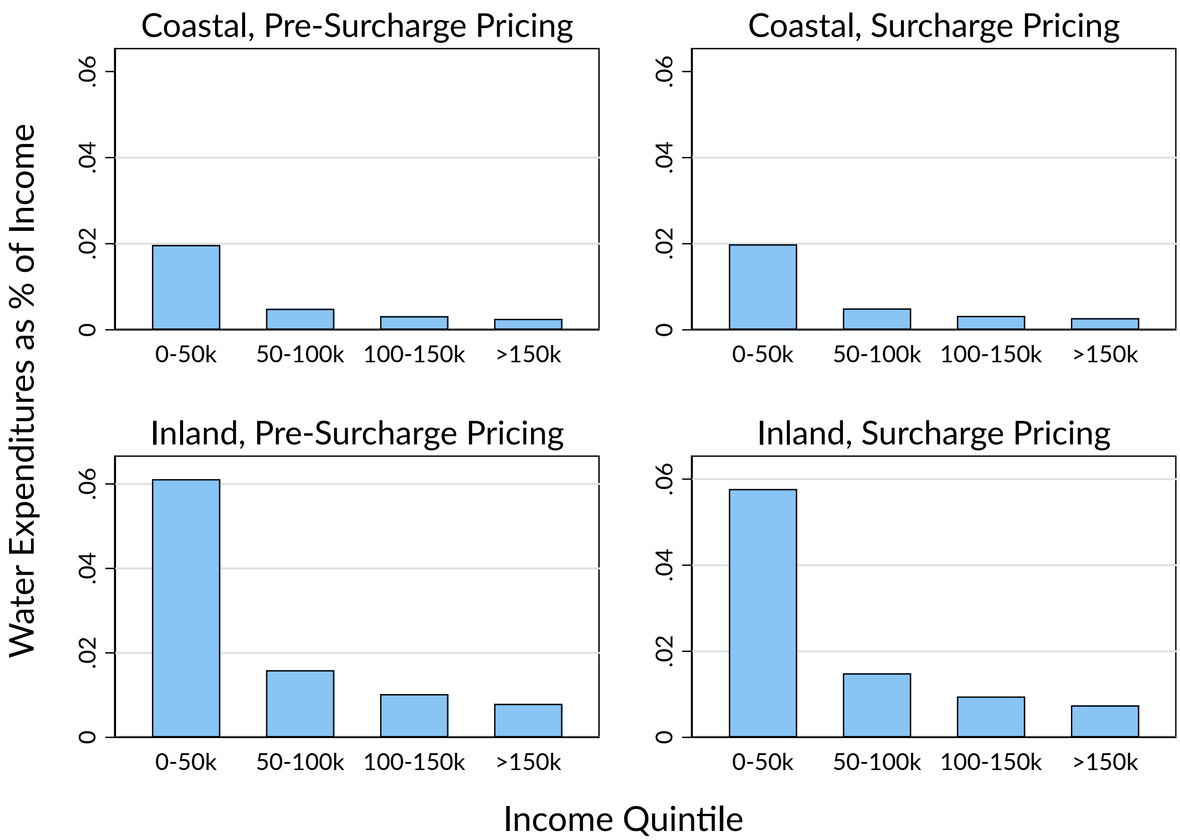



Figure A.7: Average Monthly Water Expenditures as Share of Income

**Notes:** The figure plots the percentage of monthly income that households allocate to water expenditures over discrete household income groups, calculated by taking average monthly bills and dividing by monthly income. This procedure is repeated separately for both Coastal and Inland, and separately during pre-surcharge pricing (2011-2013) and the drought surcharge pricing period (July 2015 - December 2016).

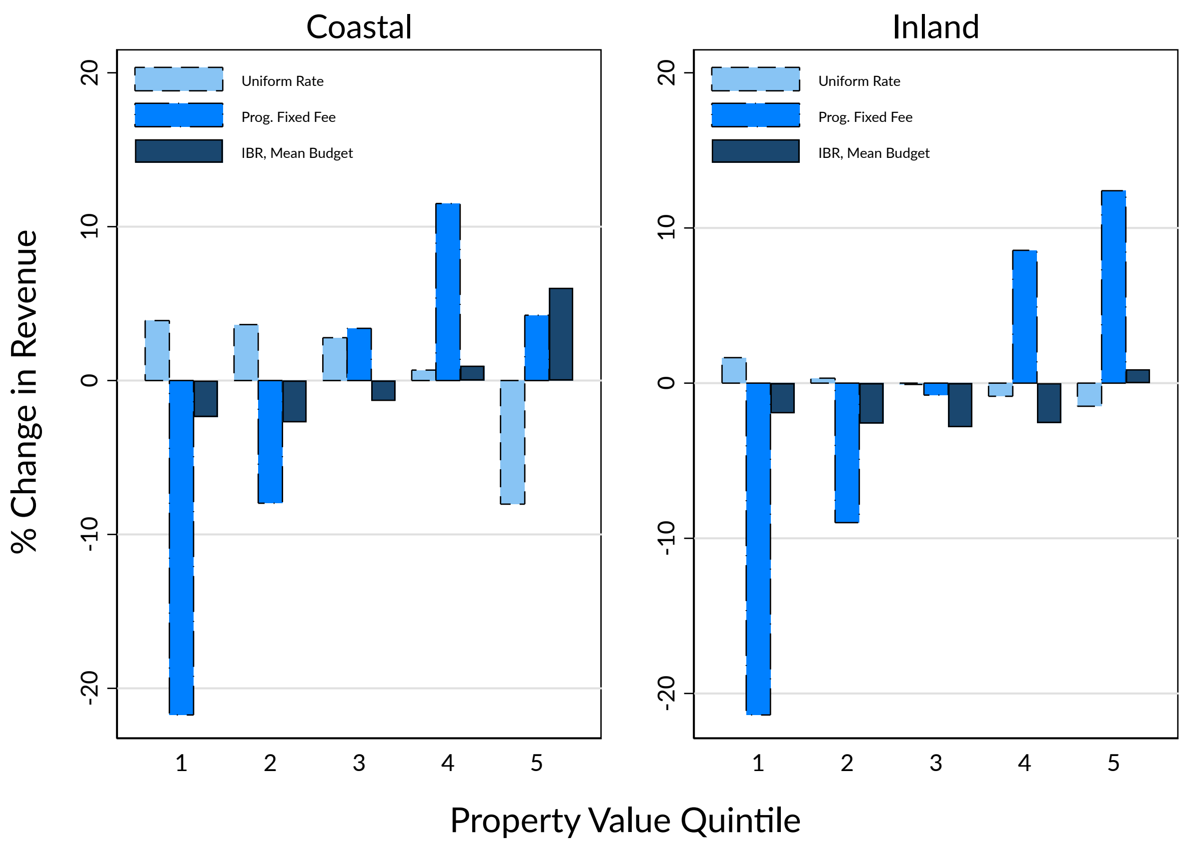



Figure A.8: Total Revenue Changes by Price-Responsiveness Assumption

**Notes:** The figure presents changes in total revenues raised from each quintile of the property value distribution when moving from BBRs to each of three alternative rate structures, respectively. Negative values indicate that less revenue is raised from that quintile of homes under the alternative structure compared to a BBR, while positive values indicate that more revenue is raised from that quintile relative to BBRs. The figure differs from Figure 6 in that we allow for a one-time adjustment of quantity in response to price changes, with a price-elasticity of demand equal to -0.5.

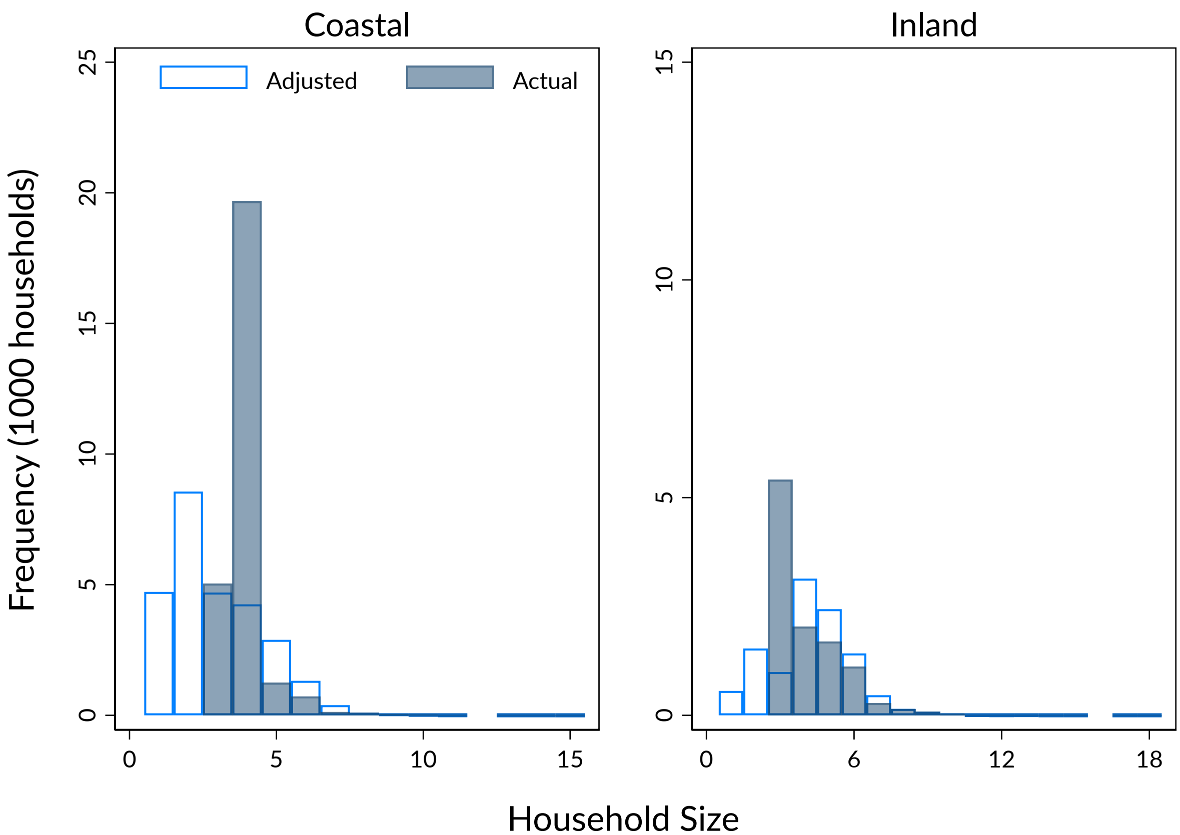



Figure A.9: Distribution of "Adjusted" Household Sizes

**Notes:** The figure presents histograms of the actual household sizes reported in the billing microdata, as well as the "adjusted" distribution of household sizes after implementing our household size correction procedure with census data. The reported or actual household size distribution is represented by the solid bars, and the adjusted household size values are represented with the transparent outlined bars.

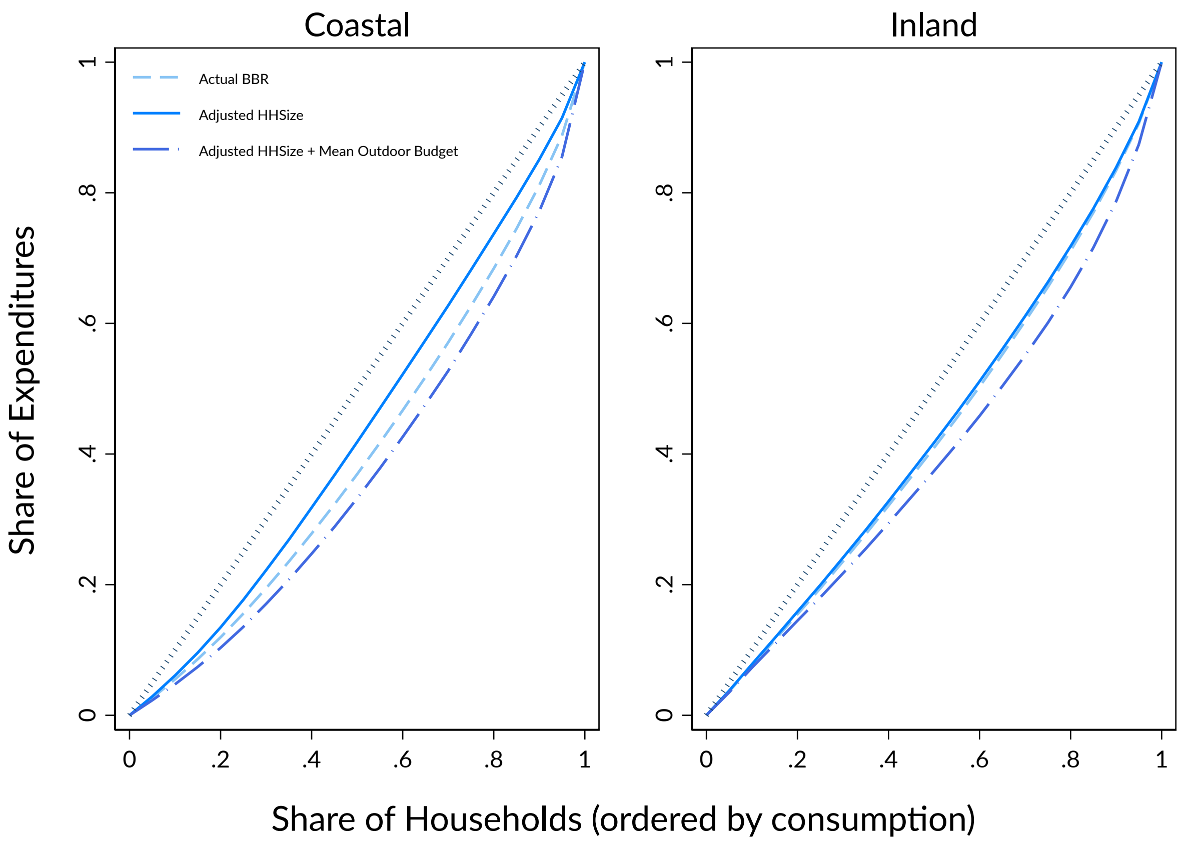



Figure A.10: Concentration Curves for Counterfactual Expenditure Shares

**Notes:** The figure presents Lorenz-style concentration curves indicating the share of water expenditures that accrue to each percentile of the household distribution ordered by consumption, separately for actual BBRs as well as the two counterfactual BBRs we develop. The time period included is the drought surcharge pricing period (July 2015 - December 2016). The 45° diagonal is plotted in the dotted black line and represents perfect equality (i.e., the bottom x% of households pay x% of water expenditures).

## A.2 Additional Tables

Table A.1: Validation Checks for Diagnostic Predictions

| Coastal | Mean |
|---|---|
| Out-of-Bag Error | 4.44 |
| Out-of-Sample RMSE, RF | 6.61 |
| Out-of-Sample RMSE, OLS | 7.31 |

| Inland | Mean |
|---|---|
| Out-of-Bag Error | 10.79 |
| Out-of-Sample RMSE, RF | 15.05 |
| Out-of-Sample RMSE, OLS | 17.61 |

**Notes:** The table presents errors for the diagnostic predictions using 2012-2013 data.

Table A.2: IV Demand Regressions, No Bootstrapping

| | Coastal | | Inland | |
|---|---|---|---|---|
| | (1) AP | (2) MP | (3) AP | (4) MP |
| Average Price | -6.49*** | | -5.57*** | |
| | (0.39) | | (1.36) | |
| Marginal Price | | -1.83*** | | -1.58*** |
| | | (0.10) | | (0.38) |
| $\epsilon$ | -1.03*** | -0.45*** | -0.61*** | -0.22*** |
| | (0.06) | (0.02) | (0.15) | (0.05) |
| Observations | 477,326 | 480,394 | 203,259 | 203,773 |
| Households | 26,995 | 27,006 | 10,840 | 10,841 |
| Household FE | Y | Y | Y | Y |
| Month-of-Sample FE | Y | Y | Y | Y |
| First-stage F-stat | 1,070 | 1,349 | 608 | 975 |

**Notes:** The table presents estimates of $\hat{\beta}$ from estimating Equation 3. The dependent variable is the difference between contemporaneous and baseline consumption, $\Delta q_{it}$. Endogenous prices are instrumented for in the first-stage using $\Delta \hat{p}_{it}$. The time period included is from July 2015 to December 2016. Columns 1 and 3 instrument for average price, while Columns 2 and 4 instrument for marginal price. All specifications include a vector of weather covariates including evapotranspiration, precipitation, temperature, and their squares. Standard errors are clustered at the household level and are presented below coefficient estimates in parentheses. *** (p-val <.01); ** (p-val <.05); * (p-val<.1).

Table A.3: IV Demand Regressions, Alternative Fixed Effects

| | Coastal | | Inland | |
|---|---|---|---|---|
| | (1) AP | (2) MP | (3) AP | (4) MP |
| Average Price | -5.44*** | | -10.96*** | |
| | (0.37) | | (1.67) | |
| Marginal Price | | -1.53*** | | -3.14*** |
| | | (0.10) | | (0.45) |
| $\epsilon$ | -0.87*** | -0.37*** | -1.19*** | -0.43*** |
| | (0.06) | (0.02) | (0.18) | (0.06) |
| Observations | 477,326 | 480,394 | 203,259 | 203,773 |
| Households | 26,995 | 27,006 | 10,840 | 10,841 |
| Household FE | Y | Y | Y | Y |
| Month-of-Sample x Zip Code FE | Y | Y | Y | Y |
| First-stage F-stat | 1,024 | 1,301 | 468 | 733 |

**Notes:** The table presents estimates of $\hat{\beta}$ from estimating Equation 3. The dependent variable is the difference between contemporaneous and baseline consumption, $\Delta q_{it}$. Endogenous prices are instrumented for in the first-stage using $\Delta \hat{p}_{it}$. The time period included is from July 2015 to December 2016. Columns 1 and 3 instrument for average price, while Columns 2 and 4 instrument for marginal price. All specifications include a vector of weather covariates including evapotranspiration, precipitation, temperature, and their squares. Standard errors are clustered at the household level and are presented below coefficient estimates in parantheses. *** (p-val <.01); ** (p-val <.05); * (p-val<.1).

Table A.4: IV Demand Regressions, Lagged Model

| | Coastal | | Inland | |
|---|---|---|---|---|
| | (1) AP | (2) MP | (3) AP | (4) MP |
| L.Average Price | -11.53*** | | -9.42*** | |
| | (0.83) | | (2.35) | |
| L.Marginal Price | | -2.92*** | | -2.86*** |
| | | (0.18) | | (0.69) |
| $\epsilon$ | -1.84*** | -0.71*** | -1.02*** | -0.39*** |
| | (0.13) | (0.05) | (0.26) | (0.09) |
| Observations | 474,460 | 477,414 | 201,267 | 201,703 |
| Households | 26,996 | 27,006 | 10,840 | 10,841 |
| Household FE | Y | Y | Y | Y |
| Month-of-Sample | Y | Y | Y | Y |
| First-stage F-stat | 400 | 577 | 217 | 301 |

**Notes:** The table presents estimates of $\hat{\beta}$ from estimating a variant of Equation 3. The dependent variable is the difference between contemporaneous and baseline consumption, $\Delta q_{it}$. Endogenous prices lagged one billing period are instrumented for in the first-stage using $\Delta \hat{p}_{it}$. The time period included is from July 2015 to December 2016. Columns 1 and 3 instrument for average price, while Columns 2 and 4 instrument for marginal price. All specifications include a vector of weather covariates including evapotranspiration, precipitation, temperature, and their squares. Standard errors are clustered at the household level and are presented below coefficient estimates in parantheses. *** (p-val <.01); ** (p-val <.05); * (p-val<.1).

Table A.5: IV Demand Regressions, Log-Log Model

| | Coastal | | Inland | |
|---|---|---|---|---|
| | (1) AP | (2) MP | (3) AP | (4) MP |
| ln(AP) | -0.29*** | | -1.75*** | |
| | (0.04) | | (0.19) | |
| ln(MP) | | -0.14*** | | -0.66*** |
| | | (0.02) | | (0.07) |
| Observations | 477,110 | 477,110 | 203,187 | 203,187 |
| Households | 26,988 | 26,988 | 10,840 | 10,840 |
| Household FE | Y | Y | Y | Y |
| Month-of-Sample FE | Y | Y | Y | Y |
| First-stage F-stat | 1,334 | 1,411 | 612 | 916 |

**Notes:** The table presents estimates of $\hat{\beta}$ from estimating a variant of Equation 3. The dependent variable is the difference between logged contemporaneous and logged baseline consumption, $ln(\Delta q_{it}) = ln(q_{it}) - ln(\tilde{q}_{it})$. Logged endogenous prices are instrumented for in the first-stage using $\Delta \hat{p}_{it}$. The time period included is from July 2015 to December 2016. Columns 1 and 3 instrument for average price, while Columns 2 and 4 instrument for marginal price. All specifications include a vector of weather covariates including evapotranspiration, precipitation, temperature, and their squares. Standard errors are clustered at the household level and are presented below coefficient estimates in parantheses. *** (p-val <.01); ** (p-val <.05); * (p-val<.1).

Table A.6: Prices Before and During Drought Surcharges

| **Coastal** | AP | $\widehat{AP}$ | MP | $\widehat{MP}$ | Bill |
|---|---|---|---|---|---|
| 1[Drought Surcharge Period] | 0.12*** | 0.13*** | 0.41*** | 1.11*** | -0.42*** |
| | (0.00) | (0.00) | (0.01) | (0.01) | (0.11) |
| Observations | 1,282,874 | 1,289,270 | 1,289,270 | 1,289,270 | 1,289,270 |
| **Inland** | | | | | |
| | AP | $\widehat{AP}$ | MP | $\widehat{MP}$ | Bill |
| 1[Drought Surcharge Period] | 0.04*** | 0.33*** | 0.08*** | 1.11*** | -8.32*** |
| | (0.00) | (0.00) | (0.01) | (0.01) | (0.32) |
| Observations | 480,161 | 481,416 | 481,416 | 481,416 | 481,416 |

**Notes:** The table presents results from a series of regressions that capture changes in prices between the drought surcharge period and the pre-drought surcharge period. Column titles represent the price variable used as the dependent variable in each specification. The primary regressor of interest is a dummy variable for the observation occurring during the drought surcharge period. The time period includes the pre-drought surcharge pricing period of 2011-2013 and the drought surcharge pricing period of July 2015 - December 2016, while omitting January 2014 - June 2015. All specifications include household and month-of-year fixed effects. Standard errors are presented below coefficient estimates and are clustered at the household level.

Table A.7: Summary Statistics for Counterfactual Rates

| Coastal | (1) Mean | (2) Mean | (3) Mean | (4) Mean | (5) Mean |
|---|---|---|---|---|---|
| Budget-Based Rate | 28.04 | 29.38 | 31.67 | 36.44 | 53.50 |
| Uniform Rate | 30.34 | 31.66 | 33.58 | 37.16 | 46.22 |
| Progressive Fixed Fee | 23.16 | 28.24 | 33.77 | 41.11 | 52.79 |
| IBR, Mean Budget | 26.22 | 27.06 | 30.47 | 36.20 | 59.14 |
| Unique Accounts | 5,402 | 5,402 | 5,400 | 5,401 | 5,401 |
| Total Billing Observations | 96,800 | 96,205 | 96,005 | 95,949 | 95,435 |

| Inland | (1) Mean | (2) Mean | (3) Mean | (4) Mean | (5) Mean |
|---|---|---|---|---|---|
| Budget-Based Rate | 88.20 | 97.53 | 100.67 | 110.56 | 141.38 |
| Uniform Rate | 91.43 | 98.57 | 100.96 | 109.31 | 138.09 |
| Progressive Fixed Fee | 71.12 | 89.48 | 100.27 | 119.71 | 157.72 |
| IBR, Mean Budget | 86.51 | 94.28 | 96.66 | 107.54 | 153.31 |
| Unique Accounts | 2,169 | 2,168 | 2,168 | 2,169 | 2,167 |
| Total Billing Observations | 40,743 | 40,798 | 40,666 | 40,751 | 40,866 |

**Notes:** The table presents summary statistics for the counterfactual bill analysis. Consumption is defined as predicted consumption in the drought surcharge period using the predictions from our random forests. Mean bills in USD ($) under each rate structure are presented for each rate structure and are broken out by quintiles of the property value distribution. Bills are defined as the variable commodity charge plus the service charge, and abstract away from other charges like sewer fees and other delivery charges that may be assessed by each utility.

# B Data Construction and Cleaning Appendix

## B.1 Raw Data Cleaning

We first import the raw data files and keep only observations in the Single-Family Residential category and in the periods during which BBRs were in place for the two utilities (July 2011 - August 2017 for Coastal and October 2011 - December 2017 for Inland). The raw billing records for Coastal contain 3,836,406 billing record observations. The Inland billing records contain 2,097,552 billing record observations. For Coastal, condos are sometimes listed as single family and sometimes as multi-family. We chose to keep both initially but then filter out buildings that are clearly master-metered apartment buildings and not apartment buildings through the use of a more descriptive property use code identifier. We then filter further by dropping accounts that use recycled water instead of standard drinking water. After these initial screens, we are left with 2,121,852 observations for Coastal and 1,025,381 observations for Inland.

We then merge each of three supplemental datasets as described in Section 3. We first merge in the U.S. Census 2015 ACS five-year estimates for household size, household race, and household income distributions at the census block group level (U.S. Census Bureau, 2015). The raw billing records were geocoded to include latitude and longitude coordinates as well as block and block group numbers which faciliitate the merge to census data. We also merge some limited demographic information received from CaDC by using customer and billing record id numbers.

Next, we merge the county assessor data from the two southern California counties in which our utilities are located. For Coastal, the assessor parcel number matches well with the assessor parcel number in the assessor data (over 99% match rate). We then drop addresses that match to more than one assessor parcel number and keep the one most likely to be the actual household (as determine by similarities in address strings). We calculate the Levenshtein difference between strings for these parcels and keep those with low scores as well as those in which street numbers of the houses match between the raw data and assessor. For Inland, the assessor parcel number did not match well with the assessor data, in part due to some data issues with extra digits at the end of numbers. String cleaning and manipulation was never able to generate higher than a 70% match rate. Even for those records that did match, in many cases hand-inspected addresses were different between the raw data and the assessor data. Therefore, for Inland we created a full address string variable by which to merge the assessor data to the billing data. This resulted in a 80% match rate. We then drop a limited number of households with more than 1 parcel number for a given address. At this stage in the data cleaning, we are left with 2,017,749 observations for Coastal and 886,529 observations for Inland.

Further, we merge in our weather variables in addition to evapotranspiration as described in the paper and from Schlenker and Roberts (2009). The data consist of daily weather measures for 2.5-by-2.5 mile grids across the contiguous 48 states. We keep records for relevant grids in southern California over the study period of our analysis (2011 - 2017). We then match customers in the billing data to their nearest grid in the daily weather data using the 'geonear' Stata package (Picard, 2012). After this, we then take each billing record and calculate the average daily maximum and minimum temperature as well as average and total precipitation based on the daily weather data for the corresponding weather grid and dates for the billing record. A small number of parcels in both data sets had missing coordinates and are dropped in this stage.

We apply four final filtering criteria to our data. We first drop a small number of remaining observations that are less than 15 days or more than 45 days, as these observations are not representative of a normal billing period that approximates a calendar month's worth of time. We then drop very large outliers in consumption and budgets. These potentially indicate months where the customers had a variance to fill a swimming pool, or potentially had a leak or other water emergency on their property. For both variables, we drop observations greater than the 99.75th percentile. Third, we apply the filtering criteria that households must have a relatively full panel ($\geq 70$ months) worth of billing records in order to guarantee that enough data is available to generate consumption predicitons. Finally, we also drop a small number of households for which there is no variability in water consumption across all months, as these are potentially households with no water consumption. After applying these filters, we are left with the final data used in the empirical analysis: 1,989,521 observations for Coastal (representing 27,006 unique households) and 789,741 observations for Inland (representing 10,841 unique households).

### B.2 Evapotranspiration and Outdoor Budget Construction in Inland

Beginning in 2016, many Inland records have missing information on indoor and outdoor water budgets. We can exactly recreate indoor budgets using the indoor budget formula, but we must rely on an estimate of the outdoor water budget. This is because we only observe aggregate evapotranspiration over the entire billing period, but Inland calculates outdoor budgets on a daily level and then aggregates them to get a total outdoor budget for the billing period. However, Inland's plant factors correspond to calendar months and most billing periods include days from two separate months. Therefore, from the raw data alone we cannot exactly re-create outdoor water budgets because we are unsure of how much evapotranspiration occurred in each calendar month of a billing period. To improve upon using the overall evapotranspiration measure, we use publicly-available data from the California Irrigation Management Information System (CIMIS, 2018) to calculate an estimate of the percentage of evapotranspiration that occurred in each month of the billing period. We then apply those percentages to the total evapotranspiration observed for the billing record, and generate two new variables for each billing record that represent the portion of the overall evapotranspiration that occurred in each calendar month of the billing record. Then, we are able to apply the correct daily plant factors to these adjusted evapotranspiration variables, and more accurately recreate outdoor water budgets.

### B.3 Price and Bill Calculations

We gather historical information about residential water rates and budget tiers from both utilities' financial records and other publicly available documents in order to merge price information with our billing records. We formally code the rate structure for each budget period using the Open Water Rate System (OWRS) developed by the California Data Collaborative. We calculate final bill amounts using the R package 'RateParser' developed by Tull (2016). This package allows users to bring in data on monthly water budgets and consumption and apply the rate structures coded in OWRS format to easily calculate total monthly bills. While the Coastal billing records did not include the final bill amount, we repeat this process for Inland despite having final bill amounts to help us ensure the accuracy of our calculations. This also indirectly helped us to confirm that our estimates of outdoor budgets discussed previously were accurate as our calculated bills were very close to the provided bill amounts. Our analysis here accounts for the fact that Coastal rounds budgets to the nearest integer, while Inland does not.

# C Empirical Framework Appendix

## C.1 Prediction Generation

The first step in our empirical analysis is the development of predictions that reflect what counterfactual consumption would have been in the absence of price and non-price conservation policies (described in Section 4). We use random forests, a machine learning algorithm commonly used in predictive exercises, to generate these predictions (Breiman, 2001). We use the `rforest` Stata package from Schonlau and Zou (2020) to implement our predictive exercise.

Our predictions use data from 2011-2013 to predict consumption in 2014-2017. An underlying assumption that we make is that random forests have the ability to predict reliably well in entirely out-of-sample years. While we expect our predictions to not match the observed consumption in 2014-2017 (due to the presence of drought policies), we do want the predictions in 2014-2017 to reliably capture the baseline consumption from 2011-2013. We test this assumption by performing a diagnostic exercise to check the ability of random forests to predict entirely out-of-sample. The core of the exercise is to limit the data to just two years, 2012-2013, and use 2012 data to predict 2013 consumption entirely out-of-sample. Since the full suite of drought policies had not been enacted, 2012 data should be able to predict out-of-sample in 2013 well. Results from this exercise are presented in Figure A.2. On average, the out-of-sample predictions in 2013 are close to the levels of actual consumption in 2013, and no consistent gap emerges between the two.

We additionally use the 2012-2013 prediction diagnostic exercises to perform other standard random forest model checks. In Table A.1, we present out-of-bag (OOB) error rates as well the out-of-sample root mean square error (RMSE) values for our diagnostic predictions compared to an alternative in which we use simple OLS models to generate predictions. OOB error rates are calculated by constructing random forest predictions for each observation in the training set using only the trees in which that observation was not included in the bootstrap sample used to develop that tree. OOB error rates are conceptually similar to errors calculated using $k$-fold cross validation in other machine learning applications such as the least absolute shrinkage and selection operator (LASSO). As expected, out-of-sample RMSE values are higher than the OOB errors for our random forest predictions. However, Table A.1 does illustrate that the random forest does buy us additional predictive accuracy over using simple OLS for predictions, as evidenced by the lower out-of-sample RMSE for random forests in each utility compared to OLS.

We conclude our diagnostic exercise by using the 2012-2013 data to tune a number of important parameters for our random forests. For each utility separately, we allow tree depth, number of predictor variables made available to the random forest, and minimum leaf size to vary over a range of reasonable values, estimate predictions, OOB errors and out-of-sample RMSE values, and select appropriate values to use for these parameters when estimating the primary predictions using the full data. We seek to minimize these errors while at the same time respecting computational constraints. For example, there is a clear tradeoff between allowing trees to grow and deeper for more predictive accuracy, and the amount of computational time it would take to estimate those deeper trees. Figure A.3 graphs OOB errors and out-of-sample RMSE values over the range of values considered for each of the three tuning parameters separately (and also separately by utility). The value we choose for each is represented by the vertical black lines, and represents our judgment of the value beyond which the benefits of additional improvements in predictive accuracy are outweighed by the cost of additional computing time. We choose final values for the tuning parameters as follows: 16 for tree depth, 15 for number of predictor variables, and 3 for minimum leaf size in Coastal; for Inland, we choose 18 for tree depth, 24 for number of predictor variables, and 3 for minimum leaf size.

Given these chosen values of the tuning parameters, we proceed to generate our out-of-sample predictions using the full study period, with 2011 - 2013 as the training period and 2014 - 2017 as the out-of-sample test period. We examine which variables contribute the most influence to shaping the predictions by inspecting standard variable importance plots that calculate each variable's contribution to predictive accuracy and present a variable-importance metric on the scale [0, 1] (with 1 being most influential). The results of this exercise are presented in Figure A.4, where the top 12 most influential predictors are presented for each utility separately. Outdoor and total water budgets are influential in both utiliities, as they send a normative signals to household about how much water consumption is "appropriate." Other influential predictors include weather variables and month and zip code dummies, especially in Inland.

Finally, we ensure that our results are not the result of some idiosyncratic feature unique to random forests by generating an alternative set of out-of-sample counterfactual predictions for 2014-2017 using a simple panel fixed effects approach. We include a vector of weather covariates and interactions and household-by-month-of-year fixed effects to generate these predictions. The time series of average monthly values is presented in Figure A.5. These predictions also reliably capture household consumption on average in the training period and replicate the observed gap between predicted and actual consumption that we observe when using random forests.

### C.2 Bootstrapping Procedure

Our initial approach of clustering standard errors at the household level does not account for the fact that our random forest predictions are estimated with error. Without correcting for this, it is likely that our clustered standard errors will be too small. To the best of our knowledge, there is not fully clear guidance from the econometrics literature on how to handle this issue, and that in practice it is common to bootstrap both the prediction and regression steps of the estimation procedure to fully account for the variance associated with our predictions (for example, the procedure described in Burlig et al. (2020).) To construct standard errors for $\hat{\beta}$ that properly account for errors associated with our predictions, we implement the following bootstrap procedure:

- Sample households with replacement up to the full number of households in each utility. Sampling a household means that all their data across years is included in the sample.
- Train the random forest using the 2011-2013 data from the bootstrap sample, and predict $\hat{q}^b_{it}$ out-of-sample in 2014-2017 for the bootstrap sample.
- Construct the predicted price change instrument $\Delta\hat{p}^b_{it}$ in the same way as before using $\hat{q}^b_{it}$.
- Estimate Equation 3 on the bootstrap sample (weighting by number of times household was sampled) and save values of $\hat{\beta}^b$
- Repeat the process $B$ times. We set $B$=500 to balance having enough bootstrap replications to capture the important variability while respecting computational constraints.
- Calculate the mean and variance of the $B$ estimates of $\hat{\beta}$, and report the bootstrapped standard error as the square root of the estimated variance.

# D Distributional Appendix

## D.1 Construction of Household Income Variable

We do not directly observe a measure of income for the households in our study. We create an estimated measure of household income to use in the construction of our water Lorenz curves presented in Section 6. To estimate income, we use the following method, incorporating both information property values from our assessor data, as well as annual household incomes from the ACS Census 2015 5-year estimates at the block group level (U.S. Census Bureau, 2015).

ACS provides estimates of the number of households in discrete income ranges at the block group level. We combine these estimates with data on the total households in the block group to create proportions of homes in each income category. For reference, the annual income categories are as follows: Less than $10,000; $10,000 - $14,999; $15,000–$19,999; $20,000–$24,999; $25,000–$29,999; $30,000–$34,999; $35,000–$39,999; $40,000–$44,999; $45,000–$49,999; $50,000–$59,999; $60,000–$74,999; $75,000–$99,999; $100,000–$124,999; $125,000–$149,999; $150,000–$199,999; and More than $200,000. To illustrate the calculation we make, consider a relatively wealthy block group that is estimated to have 200 homes overall, of which 40 homes each belong to the top five income brackets. Therefore, the proportion of homes in each income range is 0 for the lower income brackets, and 0.2 for each of the top five income brackets.

We proceed by ranking the households in each block group for both utilities by that household's observed property value. We then take the proportions calculated previously and apply them to our household rankings. Now, consider the same hypothetical block group from before. We apply the percentages calculated from the ACS data to the households in this block group that are in our data. In this example, this would results in no households being assigned to the lower income groups, and 20% of the households in our data being assigned to each of the top five income groups. We conclude by assigning each household the midpoint of the discrete income range it was assigned to. Functionally, this means that each household is assigned one of the following annual income values: $5,000; $12,500; $17,500; $22,500; $27,500; $32,500; $37,500; $42,500; $47,500; $55,000; $67,500; $87,500; $112,500; $137,500; $175,000; and $200,000.

Our procedure depends on two primary assumptions. The first assumption that the households in our data are representative of the block group as a whole, and that the income distribution illustrated by the ACS data accurately describes the income distribution of the households in our data. The second primary assumption is that property values, which we do observe in our assessor data, are correlated with income and can be used to compare households in our data, such that a household with a higher property value also has a higher income. This is a strong assumption but one we make given data limitations.

## D.2 Construction of Alternative Rate Structures

We construct counterfactual bills under three alternative rate structures: a uniform rate where the marginal price paid for each unit of water is constant, the same uniform rate coupled with a fixed service charge that varies with household income, and an IBR designed to mimic the budget tiers observed in practice. We discuss the construction of each set of alternatives in turn.

The uniform rate is the simplest of the three alternative rate structures. We begin by aggregating total volumetric revenue and total consumption in the drought surcharge pricing period. Recall that these aggregate measures are based on *predicted* consumption. We then divide total predicted revenue by total predicted consumption to calculate the single uniform rate that satisfies our assumption of revenue neutrality. For Coastal, this uniform marginal price is $1.79/CCF.

For Inland, the uniform marginal price is $2.55. These prices for both utilities fall between the Tier 2 and Tier 3 prices under the existing BBRs.

Next, we combine the uniform rate derived in the previous structure with a "progressive" fixed service charge, similar to the analysis in Burger et al. (2020). To construct a fee that varies with income, we start with our estimated household income measure defined for the Lorenz curve analysis and aggregate income utility-wide. This allows us to determine each household's share of total utility-wide income. We then aggregate total revenues from the existing fixed service charges. We conclude by multiplying each household's share of total income by the aggregate service charge revenue to determine each household's "progressive" service charge. The service charges we calculate range from $0.49 to $19.62 in Coastal, with a mean of $11.22. For Inland, the service charges range from $1.45 to $58.06, with a mean of $29.90.

We conclude by constructing a revenue-neutral IBR structure. We construct the IBR tiers by taking the average indoor and outdoor water budgets for each utility under drought surcharges and use those as the block cutoff points between Tier 1 and 2 consumption, and Tier 2 and 3 consumption, respectively. We further mimic the BBRs we observe in practice by setting 125% of the total budget as the cutoff between Tier 3 and 4 consumption, and 150% of the total budget as the cutoff between Tier 4 and 5 consumption. The functional difference between this alternative rate structure and the existing BBRs is that rates are defined utility-wide and are no longer household-specific. We then distribute predicted consumption to each of the new IBR blocks.

We then determine a schedule of prices consistent with our revenue-neutrality assumption. Since there are infinitely many combinations of prices that result in the same overall volumetric revenue, we solve a system of linear equations that includes the total revenue equation (price times quantity within each block) as well as a series of equations that maintain the ratio of prices in higher blocks to the prices in Tier 1 of the actual BBR structure. This set-up results in a unique solution that preserves the nature of an IBR structure as well as the ratio of prices in the original BBR structure. The price schedule we calculate for our alternative IBR is as follows for Coastal: $1.01 for Tier 1 consumption, $1.15 for Tier 2 consumption, and $6.29 for consumption in Tiers 3 - 5. Recall that we are mimicking drought surcharge pricing, which is why the price for all consumption above budget is constant. For Inland, the IBR price schedule is $1.96 for Tier 1 consumption, $2.29 for Tier 2 consumption, $4.38 for Tier 3 consumption, and $5.37 for consumption in Tiers 4 and 5. Note that we obtain four unique prices instead of three as with Coastal because Inland restored the Tier 3 price one year into drought surcharges. The breakpoint between our five consumption tiers are 10, 16, 20, and 24 CCF in Coastal, and 10, 36, 45, and 54 CCF for Inland.

### D.3 Counterfactual BBR Structures

Proposition 218 in California limits the extent to which local governments can assess new taxes and fees. Utilities considering changes to their rate structures must take care to not run afoul of Proposition 218 restrictions. Given this, it might be infeasible to assume that our two utilities could change to a different type of rate structure as we do in our counterfactual bill analysis in Section 6. A natural question arises from these restrictions: if other rate designs are infeasible and utilities are set on using BBRs, how can changes to the water budget formula itself affect its redistributive properties? We consider here two feasible changes to the water budget calculations.

First, we examine the assumptions that utilities make about household size for homes in their service territories. As referenced earlier, both utilities make an initial assumption about single family household sizes (3 or 4 in Coastal and 3 in Inland) that households can later update. Given that household size is a direct component of indoor budgets, this policy incentivize households with more than the assumed number of persons to update their household size with the utility and receive a larger budget. We verify this trend in the data in Figure A.9, as households do not update their household size to be smaller than the default. The solid bars represent the distribution of household sizes reported in the data, and show no households with one or two people. This points to a potential issue, as it is unlikely that this distribution of household sizes used in calculating water budgets will closely match the actual distribution of household sizes in each utility's service territory.

We use Census data on household sizes in our study areas to create an adjusted measure of household size. To do so, we sort households first by number of bedrooms then by irrigable square footage within census block groups. We assume that households that have updated their household size with the utility are "correct", and only include households that are assigned the default household size in this correction. Then, in a similar process used in our estimation of household income, we assign each ranked household an adjusted or "corrected" household size according to the distribution of household sizes in each block group. For example, if ACS says that 10% of homes in a block group are 1 person homes, we will assign the bottom 10% of our households in our ranking a household size of 1 instead of the default household size. Figure A.9 also plots this adjusted distribution in the transparent bars, showing the gap between what the observed data and what the census data imply about household sizes.

This is our first counterfactual BBR: we keep all other factors the same, but just calculate budgets using this adjusted household size. Our second counterfactual BBR focuses on another large driver of variation in water budgets: irrigable square footage of a household's lawn. Our analysis has shown that this portion of water budgets allows households with large lawns to consume more water at lower marginal prices. To correct for this, we suspend the individualized outdoor budget, and instead calculate all household outdoor budgets based on the utility-wide average irrigable square footage area. We combine these new outdoor budgets with our adjusted indoor budgets from the previous counterfactual to define a household's new budget. In both of our counterfactual BBRs, we introduce a further simplification in that we collapse our budget down to 2 tiers, with an under-budget and over-budget price.

Figure A.10 displays Lorenz-style concentration curves where we plot the share of bills paid under actual BBRs as well as our two counterfactual BBRs over the distribution of households ordered by consumption. When plotting expenditures, the lower-hanging a curve is, the more redistributive in nature it is. Our results show that only correcting the household size actually makes BBRs slightly less redistributive relative to the observed rates, indicating that the liberal household size assumptions are relatively more beneficial to lower consumption, smaller homes. Assigning all households a single average outdoor budget significantly improves the redistributive nature of BBRs relative to both alternatives, as many large households with large budgets have their outdoor budgets reduced as a result of the policy change.