Heterogeneous Responses to Price: Evidence from Residential Water Consumers *

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Abstract

Public utilities may respond to demand or supply fluctuations by adjusting prices to ration quantity. This approach's efficacy and distributional impacts depend on households' heterogeneous price sensitivity, which we estimate in a market for residential water usage. Our household-level panel data features a large change in marginal water prices and a novel measure of local hydrological stress. Contrary to prior research, we find that heavy-usage households are more price sensitive than other households, and price elasticity is largely invariant to household wealth.

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Public or regulated utilities, such as water and electricity providers, often face demand or supply fluctuations that make it difficult to satisfy all demand with a single year-round price. Utilities may respond to these challenges with rationing, either through prices or explicit usage restrictions, or by increasing capacity. In recent years, price-based rationing has gained popularity as a demand management tool (Cuthbert and Lemoine, 1996; Newsham and Bowker, 2010; Kenney et al., 2011; Mayer, Hunter and Smith, 2018). Price increases can be used to reduce quantity demanded to meet (perhaps reduced) supply while allocating the utility's product to consumers with the greatest marginal benefit. The appeal of this approach may increase in the coming decades due to aging infrastructure, changes in climate and population, and the increasing cost of creating new capacity.[1]

In this paper, we provide new insights into price-based rationing by analyzing a detailed panel of households' monthly water usage. The data allow us to describe how households of different wealth and water usage patterns respond, potentially differently, to variation in water prices, environmental conditions, and usage restrictions. Most notably, we find that heavy-usage households, regardless of wealth, are significantly more price-sensitive than other households. These findings are in contrast with the previous literature. Potential explanations for these differences include the salience and structure of the price changes we observe as well as our treatment of consumer heterogeneity.

Understanding heterogeneity in demand for residential water is important for evaluating the impact of using prices to manage demand. Water supply networks are typically designed based on peak usage, which generally occurs during the summer when up to 50% of all usage is for lawn and garden irrigation (Mayer et al., 1999; Balling, Gober and Jones, 2008; Swamee and Sharma, 2008). For price-based rationing strategies to successfully reduce water usage, price increases should have a significant impact on heavy-usage households who are likely to irrigate. Estimating heterogeneous responses to price changes is also a necessary precursor for the analysis of distributional effects.

The previous literature on water demand's price elasticity has explored heterogeneity

[1]Most of the electrical grid and over 30% of water utilities already operate at or near maximum capacity. Experts have estimated that $1 trillion are required to maintain and expand service to meet demand over next 25 years (Fynn et al., 2007; American Society of Civil Engineers, 2017; American Water Works Association, 2019).

along two dimensions, independently of one another. First, studies have explored how price responses vary with wealth, usually proxied by home value or income. These studies suggest that wealthier households have less elastic demand for outdoor water usage as well as for water usage overall (Mansur and Olmstead, 2012; Wichman, Taylor and von Haefen, 2016). Second, studies have explored heterogeneous responses by usage. Wichman, Taylor and von Haefen (2016), for instance, find that heavy-usage households with irrigation systems are generally less price sensitive.[2] Taken together, these previous results suggest that price-based policies may not be effective in reducing demand by heavy users, and may generate distributional effects by raising water expenditures by poor households.

We depart from previous work in several ways. First, our data have several advantages over those used in past studies. We observe a transition from year-round uniform pricing to seasonal pricing in which summer prices are about 40% above winter prices, and all marginal prices are constant in a household's quantity consumed. To our knowledge, previous studies of household-level water demand have not featured price shifts this large and as simple in structure.[3] Additionally, severe drought conditions during part of the sample period triggered the use of command-and-control (CAC) policies that imposed restrictions on outdoor usage. This provides an opportunity to also examine the effects of CAC policies. Finally, we use a hydrological model, calibrated to the local area, to calculate a measure of local hydrological stress (i.e., moisture available to lawns). This enables us to employ a single variable to precisely measure conditions that stimulate outdoor water usage.[4]

Second, we examine heterogeneous responses in terms of usage and wealth simultaneously instead of in isolation. This highlights the fact that both dimensions are necessary for understanding household responses, and neither is sufficient alone. Households with similar wealth levels may have different preferences for outdoor water usage, and households with comparable levels of usage may respond differently to price changes given the resources at their disposal.

[2]Wichman, Taylor and von Haefen (2016) examine how price responses vary by wealth and usage characteristics but not the interaction of the two characteristics.

[3]Seasonal pricing is also sometimes referred to as "peak-load" or "time-of-use" pricing. Previous studies of residential water demand under seasonal pricing (Renzetti, 1992; Lyman, 1992; Reynaud, 2010) have focused on aggregate demand rather than household-level demand.

[4]Previous water demand studies vary in how they model environmental factors. See Arbués, García-Valiñas and Martínez-Espiñeira (2003) or House-Peters and Chang (2011) for reviews of the literature.

Third, we characterize households' usage heterogeneity in terms of temporal patterns and levels over the course of a year. We use machine learning cluster analysis techniques to group households according to similarity in their usage. These groupings, which we call "usage profiles," identify households that likely irrigate, making use of available data without the need for costly monitoring of usage (DeOreo et al., 2011) or strong assumptions to explicitly distinguish between indoor and outdoor usage.[5] Furthermore, characterizing households in terms of usage profiles is intuitively meaningful and of practical relevance.

Our estimates of water demand shed new light on the efficacy and distributional consequences of price-based policies. In particular, we show that households that are most likely to irrigate (i.e. heavy-usage households) are more price sensitive than other households, and price sensitivity does not vary across wealth levels. For example, we find that wealthy heavy-usage households have a price elasticity of -0.384, while wealthy light-usage households have a price elasticity of 0.020, which is not statistically different from zero.[6] By contrast, the previous literature typically finds that households with higher outdoor water usage are less price sensitive than other households (Mansur and Olmstead, 2012; Klaiber et al., 2014; Wichman, Taylor and von Haefen, 2016).[7]

Why are our results different from the previous literature? One possible explanation is the pricing experiment we observe features large price changes in an otherwise simple pricing environment in which the marginal price of water does not vary with quantity consumed. Prior studies that find heavy-usage households have more inelastic demand generally have to account for marginal water prices that increase with quantity (i.e., "increasing block prices"). This leads to two challenges. First, households with greater demand face higher

[5]In water demand studies, it is often difficult to distinguish between outdoor and indoor usage. One common approach, pioneered by Howe and Linaweaver (1967), is to assume that a household's outdoor usage is equal to the difference between its usage during irrigation season and the "base usage" of winter months. In addition, water demand studies generally have not addressed household-level heterogeneity; see reviews by House-Peters and Chang (2011) and Fuente (2019). Exceptions include Renwick and Archibald (1998); Mansur and Olmstead (2012); Klaiber et al. (2014), and Wichman, Taylor and von Haefen (2016). Similar issues exist for residential energy demand; see Reiss and White (2005); Swan and Ugursal (2009); Borenstein (2012) and Auffhammer and Rubin (2018).

[6]These elasticity estimates are in the range of values that previous studies have found for areas with similar environmental conditions. Elasticity estimates tend to be greater in the western United States (Dalhuisen et al., 2003).

[7]Although elasticity estimates for irrigating households vary, they are often statistically indistinguishable from zero and, in some cases, positive.

prices, which requires researchers to resolve endogeneity concerns that can bias upward the price elasticities of heavy-usage households. Second, consumers may have difficulty understanding the schedule of increasing prices (Shaffer, 2019). Another possible explanation is our joint characterization of households in terms of both wealth and usage profiles more effectively identifies households' preferences for outdoor water usage and their price sensitivities. Indeed, we show that ignoring this heterogeneity can lead to differences in the price elasticity estimates.

We complement our elasticity estimates with descriptive evidence of transitions in usage profiles over time. This provides insight into the extent to which households make substantial changes in water usage following the introduction of higher prices. These descriptions reveal that a large share of households reduced water usage significantly after the implementation of seasonal pricing.

1 Data

1.1 Water Usage Data

The Orange Water and Sewer Authority (OWASA) in Orange County, North Carolina provided us with monthly water usage and rate data from October 1999 through September 2005 for single-family residential properties. We match this data with each property's parcel-level characteristics using Orange County Land Records' geographic information system. These characteristics include lot size, square footage, year built, assessed value of the home in 2000, and the Census Block Group.[8] During the sample period, OWASA staff recorded usage from household water meters approximately monthly, with different households' usage recorded on different days of the month. We define monthly usage for each household in terms of these "read periods." In recording households' usage data, OWASA truncates to the nearest thousand gallons the total quantity of water used during a read period.[9] Usage above a truncation point carries-over to the next read period, which effectively delays payment

[8] In OWASA's service area there are 45 Block Groups which contain, on average, about 190 households each.

[9] In our empirical analysis, we treat monthly usage as a continuous variable so that we are able to perform estimation using standard fixed effects methods.

rather than allowing some usage to be unbilled entirely.

To prepare the sample we use for empirical analysis, we remove observations that may be incomplete or contain errors. First, we eliminate households that, despite OWASA's billing designation, may not be single-family households.[10] Next, we drop households with usage data that begins later than October 1st, 1999. This insures that we observe all households for more than two years prior to OWASA implementing seasonal pricing in May 2002. We eliminate outliers by dropping households with monthly usage values that ever exceed the 99.9th percentile of usage; some of these extreme outliers are due to meter misreads or catastrophic leaks. We also drop households with zero-usage readings in 2+ consecutive periods or 12+ periods in total, in order to exclude households with frequent absences due to travel or intermittent rental activity.[11] Our final sample, summarized in Table 1, contains 4,455 households, roughly 52% of the starting data.

1.2 Water Prices

OWASA is among the first water utilities to use prices as part of a broader strategy to manage demand during non-drought periods. On May 1st 2002, OWASA replaced uniform year-round prices with seasonal prices that are higher in the summer.[12] The decision to adopt seasonal pricing was part of a longer-term plan to manage water resources and not in response to a particular event. OWASA sets the price schedule each year to cover their yearly expenses for the residential sector as a whole. Similar to many utilities, OWASA charges households a combination of volumetric and fixed fees. The volumetric portion of the bill includes separate per-unit charges for both water and sewer services. Because households are billed for both services on the same bill, we follow the literature in assuming that the effective marginal water price is the combined price for water and sewer services.

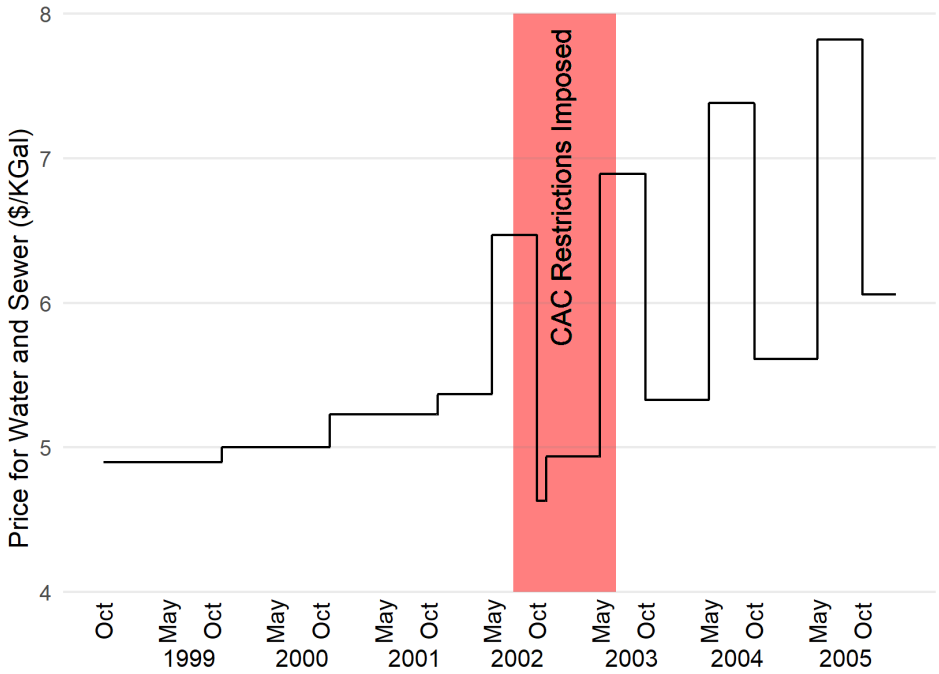
In Figure 1, we show the nominal marginal prices per thousand gallons (KGals) from

[10] For example, we eliminate customers with multiple location identifiers as they may represent households that own multiple homes or properties managed by rental agencies. We also eliminate customers whose land record information is inconsistent with a single-family property.

[11] A zero-usage reading may also be due to meter rounding for very low usage amounts, or it could indicate a water shutoff due to non-payment. Our estimation results are robust to different sample construction rules related to missing readings, including dropping households with any zero-usage months.

[12] In October 2007, OWASA transitioned to a different pricing schedule in which marginal prices increase with usage.

Figure 1: Seasonal Prices and CAC Restrictions



Notes: Prices are nominal US dollars. CAC restrictions were imposed from July 11th 2002 through June 2003. The dip in the marginal price observed in October 2002 was due to a brief administrative error.

October 1999 to October 2005. Prior to 2002, price changes were limited to small increases on October 1st of each year. The introduction of seasonal prices, which we refer to as the treatment, began in May 2002. This pricing scheme features marginal prices that are 40% greater during summer months (May-September) relative to the rest of the year. Water prices during non-summer months are largely unchanged with the introduction of seasonal prices. Fixed fees and volumetric sewer charges remained constant throughout the year. In our empirical analysis, we convert all prices to January 1999 dollars using the seasonally-adjusted U.S. city average monthly consumer price index (CPI) from the U.S. Bureau of Labor Statistics.

1.3 Command-and-Control Restrictions

Approximately two months after the implementation of seasonal pricing in 2002, drought conditions led to falling reservoir levels, triggering the use of CAC restrictions, indicated with shading in Figure 1. CAC restrictions target outdoor water usage to encourage conservation. These restrictions are determined by reservoir levels and are independent of OWASA's introduction of seasonal prices. Violations of CAC restrictions were considered misdemeanors and enforced through fines by the local townships and Orange County. OWASA implemented CAC restrictions in three stages, with stricter requirements imposed during each subsequent stage. On July 11th, 2002, the first restriction, *Stage 1*, was implemented, restricting irrigation of lawns, gardens, trees, or shrubs to three days out of each week. Approximately one month later, the second restriction, *Stage 2*, was implemented, further restricting irrigation to only one day a week. Two weeks after the implementation of *Stage 2*, OWASA implemented water supply *Emergency* restrictions as reservoir levels continued to fall.[13] This restriction prohibited the use of outdoor water for any purposes other than fire suppression or necessary emergency activities. OWASA began the process of lifting CAC restrictions after heavy rains in October 2002 ended the drought. Definitions of each CAC restriction and a timeline of their implementation are in Online Appendix C.

Following the 2002 drought, OWASA introduced new usage guidelines to encourage conservation. The guidelines encouraged the use of reclaimed or harvested water, the installation of water-saving fixtures, and reductions in some outdoor watering activity. The guidelines are similar to OWASA's *Stage 1* restrictions, but they were less widely publicized and were in effect while conservation concerns were less salient in the market.[14]

1.4 Usage Profiles and Wealth

We use Ward's agglomerative hierachical clustering algorithm (Ward, 1963) to identify yearly usage patterns during October 1999-September 2001, the two pre-treatment years that fea-

[13] At the time, OWASA was concerned that households were responding to anticipated restrictions by increasing watering before the new restrictions went into effect.

[14] The guidelines also included substantial allowances for outdoor watering of new grass and plantings, which would allow households to irrigate year-round without restriction if they put down grass seed in the spring and fall.

ture constant within-year prices and small price changes between years. We define years to coincide with how OWASA implemented price changes. Combining the two pre-treatment years to create a representative year, we apply the clustering algorithm to identify yearly usage profiles based on the amount of water used in each respective month.[15] We allow the algorithm to create three usage profiles; additional levels did not add clear value for our empirical approach. As a practical matter, we need the profiles to capture enough households so that they can be further divided by other household characteristics (i.e. wealth).[16] We illustrate the usage profiles – which we refer to as *Heavy*, *Moderate*, and *Light*– in Figure 2.[17]

The usage profiles are instructive in describing differences in how households use water over the course of the year. They intuitively describe annual usage patterns, conforming with informal classifications of residential water usage. The timing and magnitude of water usage of the *Heavy* profile, for example, is consistent with lawn care. In particular, the large quantities of water usage during peak summer months suggests outdoor irrigation, and the significant amount of usage late in the fall suggests watering of re-seeded lawns in preparation for the following summer. Conversely, the *Light* profile reflects consistently low water usage month-to-month, indicative of no outdoor water usage. Finally, the *Moderate* profile reflects usage in between the two other profiles. Relative to the *Light* profile, the *Moderate* profile has higher usage during the winter and small but distinct peaks during the summer and fall, likely reflecting occasional outdoor water use. In the discussion below we emphasize differences in overall usage volume across profiles, but the ordering of profiles would be the same if we were to emphasize differences in usage seasonality, i.e. how much more water is used in summer relative to winter.

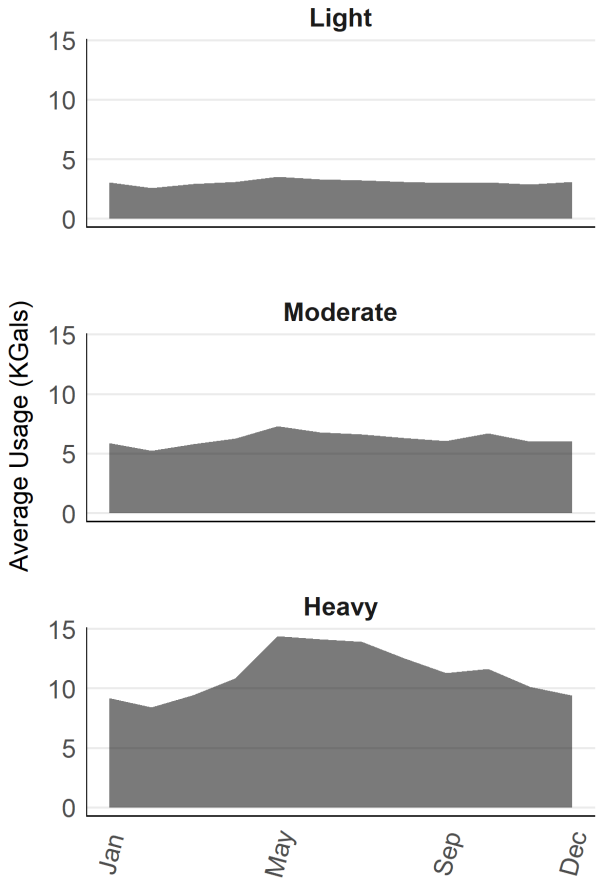
The usage profiles capture household characteristics that we do not observe directly, such as the number of people in the household or preferences for outdoor water use. We assign each household to a profile based on its usage from October 2000 to September 2001, immediately before seasonal pricing's introduction. We use k-nearest neighbors, a supervised

[15]To apply the machine learning clustering algorithm, we convert usage amounts from read periods to calendar months under the assumption that per-day usage is constant within a read period.

[16]When we experimented with adding a fourth usage profile, we found that it did not add information about the timing of water usage within the year, just its level.

[17]Ward's agglomerative hierarchical clustering method groups-together time series that are closest to each other in multivariate Euclidean space. The agglomerative coefficient, a measure of the clustering structure, for this method is 0.993 in our data, indicating a strong clustering structure.

Figure 2: Usage Profiles from Clustering



learning algorithm, to perform the match (Batista et al., 2014). As a robustness check, we redo all analyses using October 1999 to September 2000 usage to match households to profiles, and we find that our results are not sensitive to the choice of pre-treatment year. These results are provided in Online Appendix D.

We follow the convention in the literature and define household wealth using assessed value of the home (Jones and Morris, 1984; Dandy, Nguyen and Davies, 1997; Arbúes, Barberan and Villanua, 2004).[18] Specifically, we create an indicator for relative wealth based on the median assessed home value ($192,647) in the area of study in 2000.[19] We iden-

[18]Studies that have explored how price responses interact with wealth measures have used homes' assessed values or income as a proxy. Wealth may be more appropriate than income in understanding a household's ability to pays its bills, due to former capturing savings, access to credit, and other financial resources (Meyer and Sullivan, 2003).

[19]This approach is consistent with previous work. For example, Olmstead and Mansur (2012) define households with incomes and lot sizes both above the sample medians as "rich, big lot" household and those with incomes and lot sizes both below the medians are categorized as "poor, small lot."

Table 1: Usage and Parcel Characteristics

	All	***Wealth Level***		***Usage Profile***		
		Low	***High***	***Light***	***Moderate***	***Heavy***
Usage (KGals)	5.63	4.65	6.49	3.25	5.93	9.78
	(4.31)	(3.30)	(4.87)	(2.22)	(3.45)	(6.40)
House size (sq. ft.)	2346	1700	2910	1923	2444	2923
	(878.20)	(494.57)	(740.38)	(748.10)	(792.35)	(983.17)
Number of bedrooms	3.56	3.14	3.93	3.24	3.64	3.97
	(0.96)	(0.85)	(0.91)	(0.91)	(0.92)	(1.02)
Number of bathrooms	2.55	2.04	3.00	2.19	2.64	3.01
	(0.85)	(0.66)	(0.75)	(0.80)	(0.76)	(0.95)
Yard size (acres)	0.44	0.35	0.51	0.39	0.45	0.50
	(0.34)	(0.26)	(0.39)	(0.33)	(0.35)	(0.34)
House value (1000 USD)	206.65	131.37	272.31	162.93	216.27	268.20
	(98.18)	(36.68)	(87.28)	(79.08)	(90.24)	(117.67)
Year built	1975	1969	1981	1972	1977	1979
	(18)	(17)	(17)	(18)	(18)	(17)
Total households (N)	4455	2080	2375	1481	2301	673
High wealth households (N)				478	1389	508

Note: Values are means and standard deviations in parenthesis.

tify a household as *High* wealth if the home value is above the median, and *Low* wealth otherwise. Columns 2 and 3 of Table 1 summarize parcel-level household characteristics by wealth level. As indicated by the average house value for lower-wealth households ($131,369), OWASA's service area is generally wealthier than the rest of North Carolina (median home value $108,300) and the United States ($119,600).

As shown in Table 1, there is a correlation between wealth and usage, consistent with the literature (Dalhuisen et al., 2003; Harlan et al., 2009). However, 25% of the households with *Heavy* usage profiles have lower-than-median home values. In addition, the set of households with higher-than-median home values and *Heavy* usage profiles represents only 21% of wealthier households.

1.5 Environmental Conditions

Environmental conditions are important factors that drive demand for outdoor water usage such as lawn irrigation. The standard approach has been to account for this with an *ad hoc*

collection of weather variables. By contrast, we introduce a novel measure based on hydrological stress. This measure more directly captures the water needs of a household's lawn. We use a hydrology model to account for how water moves through the hydrological cycle, while also accounting for land use and vegetation cover patterns. Specifically, we introduce an index derived from a spatially-explicit eco-hydrological model known as Regional Hydro-Ecologic Simulation (RHESSys) (Tague and Band, 2004; Gao et al., 2018; Lin et al., 2019) to summarize the exogenous factors that determine lawn and soil dryness. This approach builds on previous hydrological research that has found that calculations of soil water deficits are better than weather variables (which mostly capture atmospheric conditions) at identifying periods in which plants are likely to be water-stressed in agricultural settings (Yao, 1974; Torres, Lollato and Ochsner, 2013).

We construct the index in two steps. First, RHESSys produces estimates of actual evapotranspiration and potential evaporation, which are measurements of the amount of moisture transferred from lawns to the atmosphere. The two measurements differ in that actual evapotranspiration is a conditional measure, limited by the amount of soil moisture currently available, whereas potential evapotranspiration is an unconditional measure that reflects the maximum amount of moisture that could theoretically be transferred. To produce these estimates, the model combines a high-resolution landcover database (NLCD, 2001; Pickard et al., 2015) with other model inputs (e.g. precipitation, soil water potential, air temperature, solar radiation) to model spatial and temporal dynamics of soil moisture. We calibrate and validate the model using United States Geological Survey gauges to derive estimates of soil moisture specific to lawns. In the second step, we use the resulting estimates of actual and potential evapotranspiration to produce a "water stress" index, $WS \in [0, 1]$, that captures soil conditions for each Census Block Group in OWASA's service area. A value of $WS = 0$ indicates minimally stressed (i.e., wet) conditions, and $WS = 1$ indicates maximally stressed (dry) conditions. In Appendix A, we provide further details on water stress as well as an illustration of its temporal and spatial heterogeneity. In our estimation models, we also include a measure of average temperature to capture demand for seasonal recreational water uses (e.g. water used to fill swimming pools or car washing) that water stress does not capture.

The use of water stress presumes that households water their lawns when their plants are stressed. It is possible, however, that households respond to weather variables instead. We also collect weather data and construct environmental controls similar to those typically used in the literature. In Online Appendix E, we compare our results to estimates obtained when controlling for environmental factors using *ad hoc* collections of weather variables. We show that commonly used collections of weather variables generally produce smaller estimates of price sensitivity among wealthier households with *Heavy* and *Moderate* usage profiles. We also show that is possible for collections of several weather variables to approximate our results when we use water stress. The advantage of using water stress is that it summarizes environmental factors in a single variable. This allows us to estimate differential responses to environmental factors in a parsimonious way.

2 Water Demand Estimation

2.1 Empirical Specification

We estimate a demand function for water. In considering the demand model's components and parameterization, it is useful to consider a household's constrained optimization problem. We assume that households are heterogeneous in two dimensions: their taste for landscaping and their budget constraints. In our empirical model, we allow usage profiles and house values, respectively, to proxy for these sources of heterogeneity. In addition to the utility from landscaping and the budget constraint, a household must consider the "technology" that produces healthy landscaping. This technology requires water as an input, and in general the need for watering or irrigation is greater during hot, dry weather. As the price of water increases, households with different landscaping tastes and budget constraints may respond differently to this price variation. This motivates one characteristic of our empirical specification, which allows a different price elasticity term for each usage-wealth combination. Similar to the heterogeneous effect of prices, when changes in environmental conditions affect water's productivity in maintaining a lush lawn, households of different tastes or wealth may respond differently in their water choices. This motivates a second characteristic of

our empirical specification, which allows a different response to water stress for each usage-wealth combination. Finally, households may vary in how they view CAC restrictions, which some may see as hard limits on the total amount of outdoor water to be used, while others interpret them as increasing water's price through possible fines or social pressures. Our demand model allows households with different wealth and usage profiles to have different responses to CAC restrictions.

We assume that household i's demand for water during read period t is a function of water's contemporaneous marginal price.[20] To account for demand heterogeneity, the model's parameters vary with a household's usage profile, $u \in \{Heavy, Moderate, Light\}$, and its wealth, $w \in \{High, Low\}$. For each household and combination of u and w, we define a set of indicator variables, τ_{iuw}, that are equal to one if household i has usage profile u and wealth level w, and zero otherwise. We specify demand as:

$$q_{it} = \sum_u \sum_w \tau_{iuw}\beta_{uw}p_t + \sum_u \sum_w \sum_k \tau_{iuw}\phi_{uwk}X_{it} + \sum_u \sum_w \tau_{iuw}\theta_{uw}Z_{it} + \eta_i + \epsilon_{it}, \qquad (1)$$

The dependent variable, q_{it}, is the natural log of the total quantity of water demanded by household i during read period t. The variable p_t is the natural log of the marginal price in effect during read period t. The coefficient β_{uw} therefore represents price elasticity for wealth level w and usage profile u.

The vector X_{it} records CAC restrictions, $k \in \{$*Stage 1, Stage 2, Emergency*$\}$, that were implemented during the drought. The restrictions are mutually exclusive, and we record in X_{it} the share of days restriction k was in place during each read period. The coefficient ϕ_{uwk} captures the change in usage due to CAC restriction k for households with wealth level w and usage profile u. Responses to CAC policies are identified, in part, with variation across households in exposure to restrictions per read period, due to asynchronous meter-reading and billing.

The vector Z_{it} contains controls for other factors that influence water demand during each read period. These include Census Block Group level water stress, average temperature,

[20] Alternative assumptions, used elsewhere in the literature, include the assumption that households respond to lagged prices (because they believe that prices printed in recently-received bills also apply to the current period) or they respond at the margin to an average of fixed and marginal prices (because the true marginal prices are difficult to decipher).

and the natural log of number of days in each household's read period t. We standardize the values of both Census Block Group level water stress and average temperature, demeaning then normalizing them by their standard deviations, to put them on the same scale. Z_{it} also contains variables to account for intra- and inter-year usage trends. We capture intra-year trends with a sixth-order polynomial of the average week number (values 1 through 52) of a read period.[21] We estimate separate intra-year trend coefficients for each usage-wealth type. We capture inter-year trends with a linear trend variable and the interaction of this trend variable with an indicator for summer months (May-September). Both types of trend variables are primarily identified by intra- and inter-year changes in usage prior to seasonal pricing's introduction in May 2002.[22] The intra-year trend captures seasonal variation in water demand, while the inter-year trend could be influenced by the gradual installation of modern low-usage appliances or changes in gardening and landscaping choices unrelated to water prices. Finally, we include a dummy variable that is equal to one beginning in May 2002 to account for differences in attitudes about water usage and conservation during the seasonal pricing regime.

We leverage the panel nature of the data to control for time-invariant unobserved household characteristics that may be correlated with water demand, such as the home's square footage, its numbers of bedrooms and bathrooms, its number of occupants and their average taste for water usage, and the lot size. These characteristics are absorbed by the fixed effect η_i. Lastly, ϵ_{it} is an error term that captures unobservable demand shocks that households experience during individual read periods. In estimating equation (1), we cluster standard errors at the household level.

2.2 Price and Usage Variation over Time

To estimate the price elasticity coefficients in equation (1), we rely on temporal price variation due to the introduction of seasonal pricing. During the first 2.5 years of our sample, households faced fairly stable water prices year-round, and for the sample's remaining 3.4

[21] Asynchronous meter reading and billing across households implies that we see considerable cross-household variation in average week number.

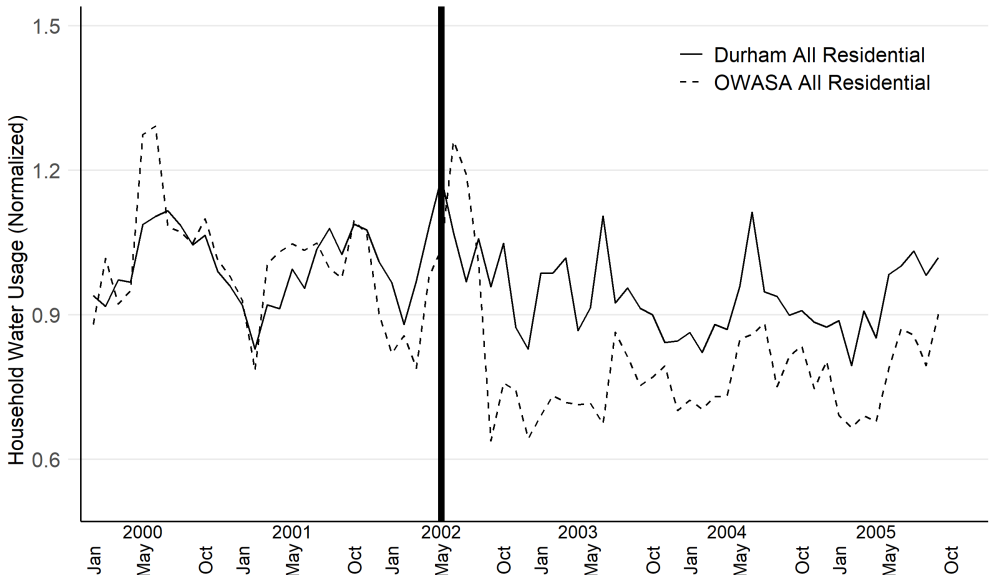
[22] Because the inter-year trend terms and household usage types are both identified by usage prior to seasonal pricing, we do not allow the trend coefficients to vary by household type.

years households' summer water prices were considerably higher and winter prices declined modestly relative to the pre-treatment nominal price trend (see Figure 1). We observe household-level data in one water market only, so we do not have the opportunity to compare treated households (facing seasonal pricing) to untreated households at the same time.

We can, however, conduct a simple comparative analysis of per-capita usage between OWASA and the city of Durham NC to investigate whether OWASA's introduction of seasonal prices coincided with region-wide usage changes that might confound our elasticity estimates. The Durham service area is adjacent to OWASA, and moreover, Durham did not have major pricing changes during the sample period. If there was a change in water usage practices in the region, we would expect to see it affect usage in both Durham's and OWASA's service areas. In Figure 3, we display monthly per-capita residential water usage in both areas. For comparability to Durham, the displayed OWASA time series is not limited to single-family households, as in our estimation sample, but this does not qualitatively affect the OWASA data. Two-thirds of Durham residential water accounts are associated with single-family households, while about 80% of OWASA accounts are single-family homes. We normalize each data series using its respective average prior to OWASA's introduction of seasonal pricing. This equalizes mean usage, which is greater in OWASA's service area, but allows for the two usage series to vary in how much larger summer usage is relative to winter.[23] Figure 3 shows that the normalized per-capita usage in OWASA and Durham are very similar in their seasonality and modest year-to-year changes up until May 2002. After OWASA introduced seasonal pricing, however, OWASA usage is consistently below Durham. For the first year of seasonal pricing, this difference includes OWASA's CAC restrictions in addition to increased summer water prices. Throughout the seasonal pricing regime, OWASA's water usage varies less between summer and winter, as we expect with seasonal prices. This suggests that our primary identification strategy – to examine within-household usage changes by OWASA customers – can provide credible estimates of demand elasticities.

[23]Usage differences reflect, in part, differences in income (55% greater in OWASA) and home value (76% greater in OWASA).

Figure 3: Water Usage in Chapel Hill and Durham



Note: The graph shows the per-capita monthly usage by all residential customers regardless of residence type in Durham (solid line) and OWASA (dashed line). Each data series is normalized using its respective average prior to OWASA's introduction of seasonal pricing.

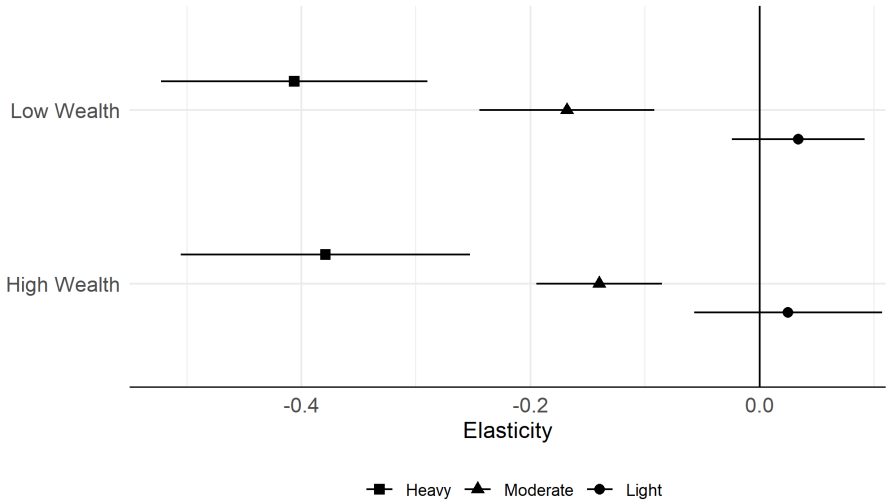
2.3 Elasticity Estimates

We show in Figures 4 - 6 the results of estimating (1) for various subsets of variables. The full set of coefficient estimates is in Table B1 in Appendix B. Starting with the price elasticity estimates shown in Figure 4, we find that there are significant differences across usage profiles. Among high-wealth households, those with *Heavy* usage profiles have a price elasticity of -0.384, while high-wealth households with *Moderate* and *Light* usage profiles have elasticities of -0.145 and 0.020, respectively. Conditional on usage profile, the price elasticities of low-wealth households are essentially the same as those of high-wealth households.[24] This finding contrasts with previous studies that have found that prices induce a larger reduction in demand among poorer households (Renwick and Archibald, 1998; Mansur and Olmstead, 2012; Wichman, Taylor and von Haefen, 2016).

Our findings on usage-level heterogeneity are valuable because they suggest that price-based rationing can be an effective tool for utilities that need to substantially reduce total

[24]We find the same qualitative pattern in elasticities if we limit the sample to the pairs of adjacent months (April and May, and September and October) when OWASA switches between winter and summer prices during the seasonal pricing regime.

Figure 4: Water Price Elasticities



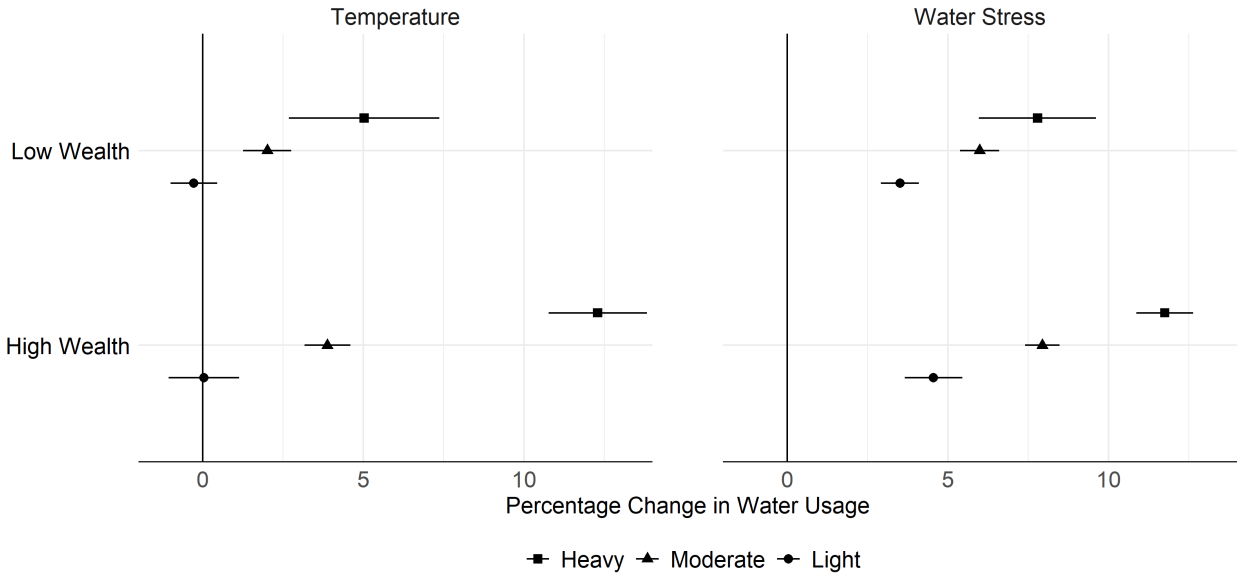
Note: Geometric shapes are point estimates and lines are 95% confidence intervals.

water usage. Water utilities such as OWASA closely monitor overall peak-season usage in making choices about capacity needs and non-price usage-reduction strategies. By definition, heavy-usage households consume a large amount of water, so a fixed percentage reduction in quantity, uniform across the population, would reduce usage gallons by the most for heavy-usage households. The price elasticity heterogeneity we document compounds this effect, as heavy-usage households reduce usage by a greater percentage on top of a greater base.

In Appendix B, we analyze the sensitivity of our results by using a variety of alternative approaches to account for inter-year trends in water usage. In particular, we estimate the summer and non-summer trends in a separate step using only data prior to seasonal pricing, as well as additional models that allow summer and non-summer trends to vary by household wealth, by an indicator of relative lot size based on the median value, and by the interaction of wealth and lot size indicators. Each model generates results that are qualitatively similar to the results in Figure 4. The price elasticities of heavy-usage households are significantly larger than price elasticities of moderate-usage households, which in turn are larger than light-usage households.

In addition to documenting heterogeneity in price elasticities, we find that households vary in their responses to environmental factors; see Figure 5. Responses to water stress and temperature increase in wealth and usage, with high-wealth heavy-usage households

Figure 5: Effect of Environmental Factors on Water Usage



Note: Point estimates (geometric shapes) are percentage change in water usage per standard deviation increase in environmental factors. Lines are 95% confidence intervals.

having significantly greater responses than all other usage and wealth types. light-usage households, as expected, are relatively unresponsive to variation in environmental conditions. This heterogeneity provides an additional opportunity for our model to capture preference variation for outdoor water usage, and therefore appropriately capture households' responses to water prices.

To understand how our approach to environmental factors supports our estimation of price elasticities, consider the potential bias in price sensitivity that would follow from assuming homogenous responses to these factors across usage profiles. With this restriction, we would under-estimate heavy-usage households' responses to hot and dry weather while over-estimating light-usage households' responses. Environmental stress occurs at the same time of year as increased prices, so uncaptured variation in weather responses will spill over to estimates of price elasticities. In particular, if heavy-usage households' weather-related increased usage is not explained by their responses to summer weather conditions, then the model attempts to fit their behavior through biased price sensitivities that are too small. This source of bias could play a role in some previous studies' findings of relatively low

price elasticities for households presumed to irrigate.[25] Likewise, homogeneous responses to environmental factors will ascribe too-strong weather responses to light-usage households with little interest in outdoor water usage. When the restricted model predicts light-usage households should moderately increase usage in response to summer weather (when the true responses are closer to zero), the model will compensate by ascribing the absence of increased usage to strong price sensitivity. To demonstrate these effects in our setting, we re-estimate equation (1) while assuming homogeneous responses to water stress and weather. The results, which are in Appendix Table B3, show that light-usage households appear more price elastic than in our main specification, and heavy-usage households appear less elastic.

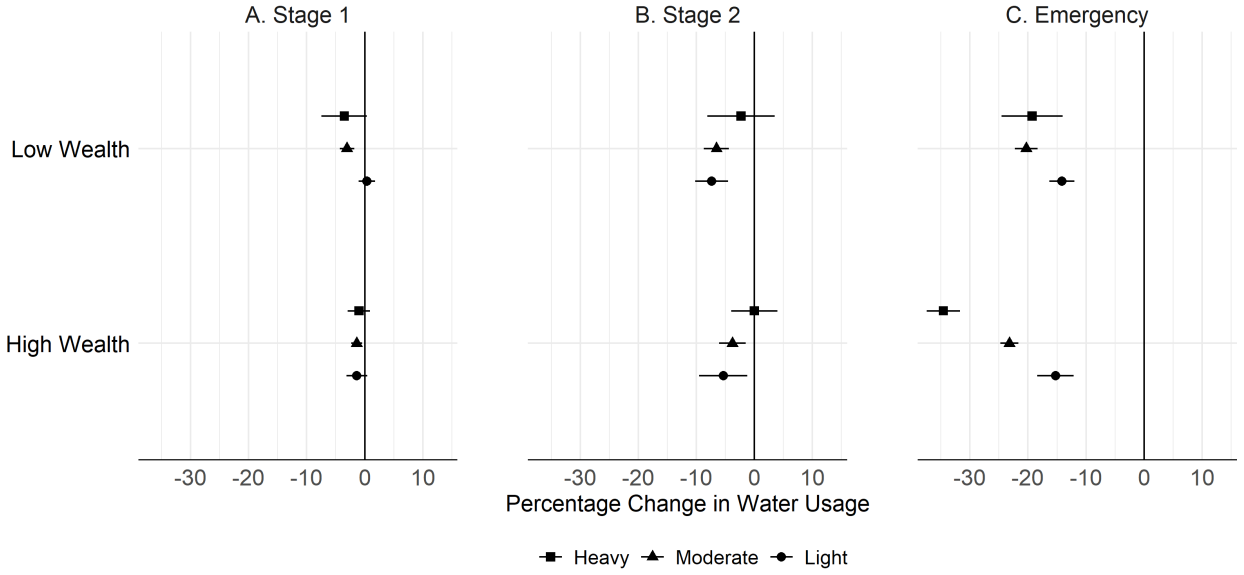
In Figure 6 we turn to the effects of CAC restrictions. The *Stage 1* and *Stage 2* restrictions had relatively modest impacts on water usage, and these effects are largely similar across usage profiles and wealth. The *Stage 2* restriction appear to register fairly weak responses by heavy-usage households, who may have felt an incentive to increase water usage in anticipation of the stricter *Emergency* restriction that followed. Households' responses to the *Emergency* restrictions were substantially larger than to the other CAC policies. heavy-usage high-wealth households, which is the group most likely to engage in regular lawn irrigation, had the largest reductions in usage under *Emergency* restrictions. While the *Emergency* restrictions, like seasonal prices, induce heavy-usage households to reduce (likely) outdoor water usage, weaker restrictions appear less successful in generating responses among heavy-usage households.

3 Additional Evidence on Usage Profiles

For the elasticity estimation conducted in Section 2, we grouped households according to usage profiles based on the households' activity prior to seasonal pricing. Though the results suggest that heavy-usage households were most sensitive to price, the way in which these households reduced usage is unclear. In this section, we examine how households' consumption profiles may transition away from their initial classification and begin to resemble other

[25] The same issues apply to settings with increasing-block pricing, a policy in which marginal prices rise with usage. When households on increasing-block pricing respond to hot and dry weather by increasing outdoor watering, their marginal prices rise.

Figure 6: Effect of Command and Control Policies on Water Usage



Note: Point estimates (geometric shapes) are the percent change in water usage due to command and control restrictions. Lines are 95% confidence intervals. Percent changes are calculated from the OLS coefficients using the Halvorsen-Palmquist-Kennedy approach to interpreting indicator variable coefficients in semi-log specifications (Jan van Garderen and Shah, 2002).

usage profiles over the treatment period. This exercise provides supplementary information about the effects of seasonal pricing on usage. In examining the impact of pricing and restrictions on consumers with a specific intial wealth-usage combination, we continue to refer to them by their initial classification. This information is relevant to water utilities, which are concerned with both price elasticities and peak-usage timing when setting policies for reservoir management (e.g. Zeff and Characklis, 2013; Zeff et al., 2016). We use a k-nearest neighbors algorithm to match each household's usage in each year to one of the three usage profiles previously identified (*Heavy* *Moderate* and *Light*).

We start by providing in Table 2 the fractions of households in each usage profile over time. For example, Panel A shows that, in the first year of the sample, 34% of households had *Light* usage profiles. This fraction stayed relatively constant for two more years before increasing to about 45%. Overall, the fractions are generally stable in the sample's first couple of years, move around in the middle two "transition years" – October 2001-September 2002 and October 2002-September 2003 – and then are generally stable at a new level in the sample's final years. These patterns suggest a qualitative shift in usage following the

Table 2: Usage Profile Shares

	Light	Moderate	Heavy
Panel A	*All Households (N=4455)*		
Oct99-Sep00	0.34	0.49	0.17
Oct00-Sep01	0.33	0.52	0.15
Oct01-Sep02	0.34	0.49	0.17
Oct02-Sep03	0.49	0.44	0.07
Oct03-Sep04	0.45	0.44	0.10
Oct04-Sep05	0.45	0.45	0.10
Panel B	*Lower Wealth Households (N=2080)*		
Oct99-Sep00	0.48	0.43	0.09
Oct00-Sep01	0.48	0.44	0.08
Oct01-Sep02	0.49	0.43	0.08
Oct02-Sep03	0.61	0.35	0.04
Oct03-Sep04	0.59	0.36	0.05
Oct04-Sep05	0.59	0.37	0.04
Panel C	*Higher Wealth Households (N=2375)*		
Oct99-Sep00	0.21	0.55	0.24
Oct00-Sep01	0.20	0.58	0.21
Oct01-Sep02	0.21	0.54	0.25
Oct02-Sep03	0.37	0.52	0.11
Oct03-Sep04	0.34	0.51	0.15
Oct04-Sep05	0.33	0.52	0.15

introduction of seasonal pricing. Panels B and C show that a similar effect holds within both high- and low-wealth households.

The two transition years are particularly interesting because they were affected by the introduction of seasonal prices, the onset of drought, and the implementation of CAC restrictions. Although we do not explicitly decompose these various effects on how households sort into usage profiles, it is important to note that there are two opposing forces at play during the summer months of seasonal pricing's first year (October 2001-September 2002). On one hand, the onset of drought conditions put upwards pressure on usage. From Section 2, we expect that this "drought effect" would primarily affect households with outdoor usage, as drier conditions increase watering needs for landscaping. On the other hand, the implementation of higher seasonal prices and CAC restrictions put downward pressure on

usage. For the full population (Panel A), we note a small, but noticeable, increase in the fraction of households with *Heavy* usage profiles during the transition years, and essentially no change in the fraction of households with *Light* usage profiles. These patterns suggest that the upward pressure exerted by the drought was generally greater than the downward pressure exerted by increased prices. Consistent with the results in Section 2, panels B and C show that the "drought effect" was particularly strong among high-wealth households.

In the following year (October 2002-September 2003), changes in usage profiles reveal large, observable decreases in usage. Since the drought officially ended in October 2002, these changes can be attributed to either seasonal prices or CAC restrictions. In particular, CAC restrictions were in place from October through the end of June, which would have affected the ability to irrigate during critical periods. We observe small increases in *Heavy* usage profiles between October 2002-September 2003 and October 2003-September 2004, suggesting a return to outdoor water usage following the lifting of the most stringent CAC restriction. Panels B and C indicate that high-wealth households increased usage more strongly than low-wealth households.

To shed additional light on the reduction in usage after the implementation of seasonal pricing, we report in Table 3 changes in household-level usage profiles relative to usage profiles in the year prior to treatment (October 2000-September 2001). We describe how to understand the entries in this table using the transitions of households with *Heavy* usage profiles. As shown in the "Oct00-Sep01" row, 673 households were classified as having a *Heavy* profile during October 2000-September 2001. Of these households in the "Oct00-Sep01" row, 75% were in that same profile the following year ("Oct 01-Sep02"), while 24% moved to *Moderate*, and 1% moved to *Light*. The next row, labeled "Oct02-Sep03," shows that 56% of initially heavy-usage households in "Oct00-Sep01" row were in the *Moderate* profile during the second year of seasonal pricing. Among households identified as *Moderate* prior to seasonal pricing, many more reduced their usage to *Light* than increased to *Heavy*. Similarly, relatively few households initially identified as *Light* moved to a heavier usage profile. We provide a table of transitions by wealth in Online Appendix F.

The information in Table 3 corroborates the finding that there seems to have been a permanent downward shift in usage for many households. It also provides further insight

Table 3: Transitions in Usage Profiles

Oct00-Sep01	*Light (N=1481)*			*Moderate (N=2301)*			*Heavy (N=673)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct01-Sep02	0.82	0.17	0.00	0.12	0.76	0.11	0.01	0.24	0.75
Oct02-Sep03	0.89	0.11	0.00	0.35	0.62	0.03	0.05	0.56	0.39
Oct03-Sep04	0.86	0.13	0.01	0.31	0.63	0.06	0.04	0.49	0.46
Oct04-Sep05	0.85	0.14	0.01	0.31	0.64	0.06	0.06	0.49	0.44

Note: The table above shows the proportion of users of in each initial usage profile whose consumption best matches each profile in the subsequent four years.

into the overall impact that seasonal pricing had on usage. In particular, the adoption of seasonal pricing was effective at reducing usage during peak summer months, resulting in observable decreases in *Heavy* usage profiles among both high- and low-wealth households. Examining transitions also provides additional information on the effects of price that were not detectable in Table 2 during the onset of drought conditions. In particular, we observe some households increasing usage and others decreasing usage in the "Oct01-Sep02" row. This would suggest that increased prices may have been effective at mitigating the effect of drought on usage, although some of these decreases may have been attributable to CAC restrictions.

4 Conclusion

Water utilities are increasingly using price-based demand management strategies as an alternative to infrastructure expansion. Evaluating these strategies requires an understanding of the consequences of price increases. In this study, we estimate demand for residential water using household-level panel data. Our data allows us to estimate elasticities that vary by both household wealth and usage profile. Our results indicate that households with heavier usage profiles are more price-sensitive than light-usage households, for any wealth level. Relative to previous research, these results provide a more optimistic assessment of the utilities' ability to use prices to reduce water consumption by heavy-usage households.

We complement the analysis with an examination of how households are matched to usage profiles over time. Following the introduction of higher marginal prices during summer

months, a large fraction of households with *Heavy* usage transitioned to usage profiles with lower and flatter usage. Moreover, we observe similar transition patterns across wealth levels.

Our findings have implications for several areas of related research. First, from the perspective of a water utility, the effect of a price change on revenues is an important consideration because utilities tend to recoup a large percentage of their fixed costs from variable charges (Beecher, 2010). Second, water utilities may be concerned with the welfare impacts of higher prices on various customer classes. In contrast to previous findings, we show that poorer households have similar demand elasticities as wealthier households. This provides the basis for future research exploring welfare implications of price changes and the affordability of water services.

Appendices

A Deriving the Water Stress Index

Previous studies of water demand have taken a variety of approaches in modeling relevant environmental factors. The most common controls used are measures of precipitation (Moncur, 1987; Renwick and Archibald, 1998; Martínez-Espiñeira and Nauges, 2004; Roseta-Palma et al., 2013) or a combination of precipitation and temperature measures (e.g. Taylor, McKean and Young, 2004; Gaudin, 2006; Wichman, 2017). Some studies have instead relied on measures of evapotranspiration (e.g. Hewitt and Hanemann, 1995; Dandy, Nguyen and Davies, 1997; Olmstead, Hanemann and Stavins, 2005). Many additional measures – such as wind speed, minutes of sunshine, and temperature differences relative to some threshold – have also been used.[26] Some recent demand estimation studies in western states have made use of satellite imagery data to calculate a Normalized Difference Vegetation Index (NDVI), a measure of landscape "greenness" to represent demand (e.g. Wolak, 2016; Brent, 2016; Clarke, Colby and Thompson, 2017).

In contrast to these approaches, we create a water stress index using the RHESSys model.[27] The advantage of this model is that it uses elements of ecosystem models (e.g. BIOME-BGC (Running and Hunt Jr, 1993) and CENTURY (Parton et al., 1987)) to model spatial and temporal dynamics of soil moisture available to lawns (the top 20 cm of soil). To do this, we first provide the RHESSys model with highly detailed spatial information to partition the landscape into forest, roads, rooftops, impervious surfaces, wetlands, pasture/agriculture lands, and lawns.[28] We then model surface and subsurface water flowpaths over the watershed. Outputs of RHESSys relevant to this study includes catchment-scaled

[26] Though typically weather variables are included as linear terms, Maidment and Miaou (1986) argue that the effects of weather may be nonlinear, as the effects of rainfall, for example, diminish over time. Martínez-Espiñeira (2002) argues that the number of rainy days can have a psychological impact therefore can have a greater impact on water demand.

[27] RHESSys has been widely used to model spatially distributed soil moisture, evapotranspiration, surface and subsurface runoff, carbon and nitrogen cycling in different biomes and under different climate and land use change scenarios (Band et al., 1993; Hwang, Band and Hales, 2009; Miles and Band, 2015; Bart, Tague and Moritz, 2016; Hanan, Tague and Schimel, 2017; Gao et al., 2018; Lin et al., 2019).

[28] We use land use landcover information at a resolution of 1 meter from the Environmental Protection Agency's EnviroAtlas (Pickard et al., 2015).

streamflow, patch-scaled (30 m) soil moisture, and patch-scaled vegetation water demand and evapotranspiration.

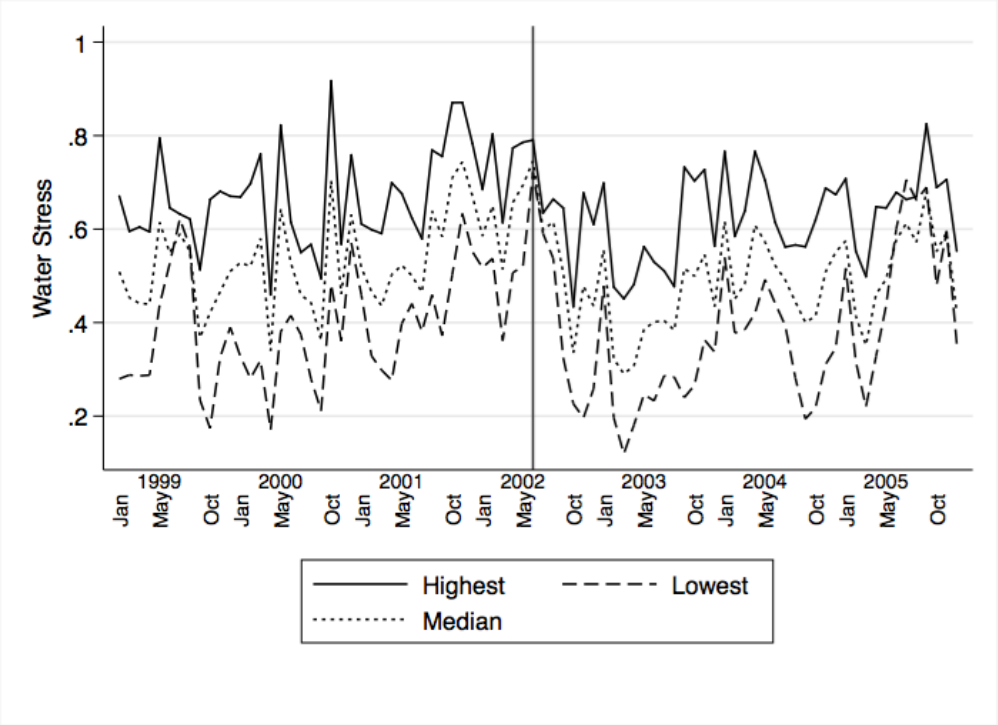
Using data from USGS gauges in the OWASA service area, we calibrate parameters related to hydrologic conductivity (water transport rate in soil columns) in our model using information for 2000-2004 and validate the model using information for 2007-2009.[29] We conduct Monte Carlo simulations to generate predictions of streamflow/catchment runoff using these parameters. These predictions are then compared to the observed streamflow in order to find the set of conductivity parameters that best represents the area under study. Model fit is evaluated using the weekly Nash–Sutcliffe model efficiency coefficient (NSE), both logged and in levels.[30] For each of these simulations, we summarize model outputs as an index, given by $WS_r = 1 - \xi^a/\xi^p$, that captures the lack of moisture available to lawns. In this equation, ξ^a represents actual evapotranspiration and ξ^p represents potential evapotranspiration. We create two versions of the variable at different spatial scales: a Census Block Group specific measure (used in the main analysis) and another at the regional (watershed) level. Figure A1 graphically represents the spatial and temporal variation in the Census Block Group water stress variable.

[29] We calibrate the model using low streamflow conditions due to drought conditions during 2001-02 and high streamflow that resulted from the extreme wet event in the latter part of 2002. Other time periods provide information on "normal" streamflow conditions. We validate the hydrological model using 2007-2009, a time period in which another drought occurred.

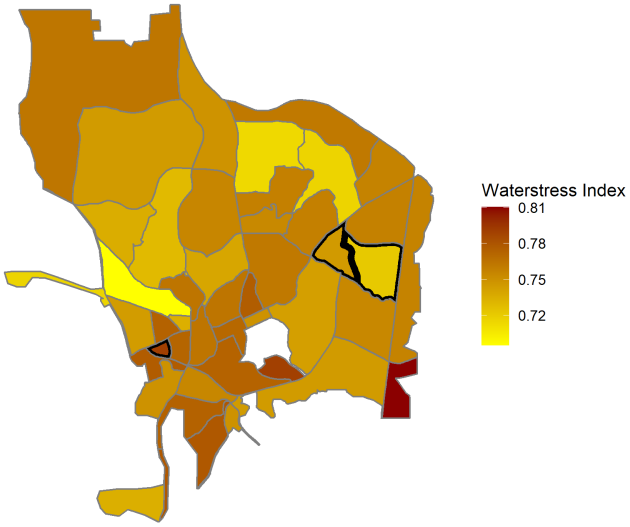
[30] Comparisons of predicted to observed streamflow require consideration of how predictions perform under various flow events (high vs. low). The NSE coefficient in levels provides information on model fitness for high flow events whereas the log transformed NSE coefficient provides information on model fitness for low flow events. High weekly and log-weekly NSE values are desired.

Figure A1: Water Stress

(a) Water Stress for Three Census Block Groups: 1999-2005



(b) Water Stress During June 2002 for all Census Block Groups



Notes: "Highest" refers to the block group with the highest average water stress during the period, "Median" the block group with the median average water stress and "Lowest" the block group with the lowest average water stress. The vertical line indicates the date for which water stress is shown for all block groups in Figure A1(b). The block groups with bold boundaries correspond to the three block groups in Figure A1(a).

B Demand Estimation Results

Main Specification

The results from estimating (1) are in Panel A of Table B1. For comparison, we also analyze a model without any heterogeneous effects:

$$q_{it} = \beta_j p_t + \sum_k X_{it}\phi_{kj} + Z_{it}\theta_j + \eta_i + \epsilon_{it}. \tag{2}$$

The results from estimating (2) are in Panel B in Table B1.

Table B1: Estimation results

	Price	Stage 1	Stage 2	Emerg.	WS	Temp.
Panel A: Main Results						
Low wealth, light usage	0.0292	0.0043	-0.0783	-0.1491	0.0355	-0.0034
	(0.0300)	(0.0078)	(0.0153)	(0.0130)	(0.0030)	(0.0037)
Low wealth, moderate usage	-0.1731	-0.0309	-0.0733	-0.2216	0.0603	0.0194
	(0.0394)	(0.0070)	(0.0132)	(0.0131)	(0.0031)	(0.0038)
Low wealth, heavy usage	-0.4111	-0.0349	-0.0290	-0.2098	0.0783	0.0496
	(0.0598)	(0.0202)	(0.0299)	(0.0340)	(0.0093)	(0.0120)
High wealth, light usage	0.0198	-0.0130	-0.0635	-0.1593	0.0460	-0.0003
	(0.0423)	(0.0100)	(0.0231)	(0.0191)	(0.0046)	(0.0056)
High wealth, moderate usage	-0.1450	-0.0133	-0.0489	-0.2571	0.0799	0.0382
	(0.0285)	(0.0056)	(0.0122)	(0.0107)	(0.0027)	(0.0037)
High wealth, heavy usage	-0.3842	-0.0088	-0.0096	-0.4173	0.1179	0.1223
	(0.0650)	(0.0099)	(0.0200)	(0.0222)	(0.0045)	(0.0078)
Panel B: No Heterogeneity						
All	-0.1298	-0.0101	-0.0542	-0.2273	0.0670	0.0317
	(0.0259)	(0.0033)	(0.0067)	(0.0063)	(0.0015)	(0.0020)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. The "WS" and "Temp" columns contain response to water stress and average temperature, respectively. In addition to the variables displayed in this table, the model includes a dummy variable for the post-seasonal pricing period and interactions of usage type and wealth indicators with log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage, for which results are reported in the "Baseline" column of Table B2. Standard errors, clustered at the household level, are in parentheses.

We assess our results' sensitivity to different approaches to usage trends. In addition to our main specification, we estimate several alternative specifications and report the results in Table B2, where Panel A contains trend coefficients and Panel B contains price elasticities. The "Baseline" column reports the inter-year trend estimates from our main specification and repeats the elasticity estimates from Table B1 Panel A. The "Two-Step" column reports trend coefficients from a model that uses data prior to seasonal pricing (May 2002) and homogeneous coefficients for all households, as in equation (2). We use these estimates to de-trend the usage data of the seasonal pricing regime, and we estimate an adapted version of equation (1) to obtain elasticity estimates. The intuition behind the two-step is model is that the pre-seasonal pricing portion of the sample period should pin-down the inter-year usage trends, and by restricting the data to this period we avoid confounding the trends with other sources of temporal variation during the seasonal pricing regime. In the remaining columns of Table B2, we explore specifications that allow usage trends to vary with permanent household characteristics that could be correlated with water demand. The "Wealth" column allows for separate inter-year summer and non-summer trends for high- and low-wealth households within equation (1). The "Lot Size" column estimates separate trends for households above and below the OWASA median lot size. The "Wealth $\times$ Lot" column estimates separate trends for each combination of wealth and lot size indicators. In all cases, the elasticity estimates in Table B2 Panel B are qualitatively the same as our Baseline results. The "Two-Step" elasticities are more negative than the Baseline results but retain the same ordering across usage types while being invariant to wealth. The remaining elasticity results, using combinations of wealth and lot size, are quantitatively nearly identical to the Baseline results.

Table B2: Estimation results

	Baseline	No Trend	Alternative Specifications		
Panel A: Trend coefficients					
Year trend	-0.0429	-0.0325	-0.0388	-0.0385	-0.0383
	(0.0015)	(0.0018)	(0.0020)	(0.0019)	(0.0024)
Summer trend	0.0055	0.0148	-0.0075	0.0030	0.0011
	(0.0020)	(0.0025)	(0.0023)	(0.0020)	(0.0027)
Year trend, high wealth	.	.	0.0013	.	-0.0004
	.	.	(0.0027)	.	(0.0032)
Summer trend, high wealth	.	.	0.0080	.	0.0038
	.	.	(0.0040)	.	(0.0041)
Year trend, large lot	.	.	.	-0.0087	-0.0014
	.	.	.	(0.0023)	(0.0035)
Summer trend, large lot	.	.	.	0.0059	-0.0111
	.	.	.	(0.0015)	(0.0046)
Year trend, high wealth, large lot	.	.	.	.	0.0023
	.	.	.	.	(0.0021)
Summer trend, high wealth, large lot	.	.	.	.	0.0048
	.	.	.	.	(0.0029)
Panel B: Price elasticities					
Low wealth, light usage	0.0292	-0.0624	0.0444	0.0200	0.0351
	(0.0300)	(0.0221)	(0.0342)	(0.0300)	(0.0344)
Low wealth, moderate usage	-0.1731	-0.2688	-0.1579	-0.1818	-0.1670
	(0.0394)	(0.0306)	(0.0451)	(0.0393)	(0.0455)
Low wealth, heavy usage	-0.4111	-0.5051	-0.3964	-0.4196	-0.4058
	(0.0598)	(0.0596)	(0.0612)	(0.0600)	(0.0618)
High wealth, light usage	0.0198	-0.0864	0.0031	0.0119	-0.0002
	(0.0423)	(0.0361)	(0.0488)	(0.0426)	(0.0490)
High wealth, moderate usage	-0.1450	-0.2497	-0.1610	-0.1526	-0.1634
	(0.0285)	(0.0193)	(0.0371)	(0.0291)	(0.0374)
High wealth, heavy usage	-0.3842	-0.4915	-0.4003	-0.3904	-0.3993
	(0.0650)	(0.0556)	(0.0770)	(0.0661)	(0.0776)

Notes: The "Baseline" column matches the specification in Table B1 Panel A. The "Wealth," "Lot Size," and "Wealth × Lot" specifications are identical to "Baseline" with the exception of the inter-year trend variables with coefficients reported in Panel A. Standard errors, clustered at the household level, are in parentheses. The "Two Step" column's trend coefficients are estimated using data pre-dating seasonal pricing, and we use these estimates to de-trend the usage data and obtain the Panel B estimates in a model identical to the "Baseline" specification. Standard errors are calculated using a bootstrapping procedure to account for sampling error.

Ignoring Heterogeneous Impact of Environmental Factors

We estimate a model in which the impact of environmental factors is not allowed to vary by either wealth or usage profiles, which we implement through a restriction on the appropriate θ_{uw} values in equation (1). The estimation results are in Table B3. Compared to Panel A in Table B1, elasticity estimates for high-wealth household are smaller while those for low-wealth households are larger for households with *Moderate* and *Heavy* usage profiles. Elasticity estimates under this specification are larger for both high- and low-wealth households with *Light* usage profiles.

Table B3: Estimation results with homogeneous effects of environmental controls

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.0499	0.0399	-0.0390	-0.1600
	(0.0291)	(0.0075)	(0.0147)	(0.0129)
Low wealth, moderate usage	-0.1876	-0.0216	-0.0636	-0.2261
	(0.0378)	(0.0069)	(0.0127)	(0.0127)
Low wealth, heavy usage	-0.3599	-0.0490	-0.0417	-0.2008
	(0.0522)	(0.0197)	(0.0302)	(0.0317)
High wealth, light usage	-0.0392	0.0131	-0.0328	-0.1723
	(0.0410)	(0.0095)	(0.0216)	(0.0188)
High wealth, moderate usage	-0.1090	-0.0257	-0.0659	-0.2536
	(0.0274)	(0.0056)	(0.0118)	(0.0103)
High wealth, heavy usage	-0.1869	-0.0747	-0.0817	-0.3718
	(0.0591)	(0.0101)	(0.0192)	(0.0200)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. In addition to the variables displayed in this table, the model includes interactions a dummy variable for the post-seasonal pricing period and of usage type and wealth indicators with: water stress, temperature, log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage. Standard errors, clustered at the household level, are in parentheses.

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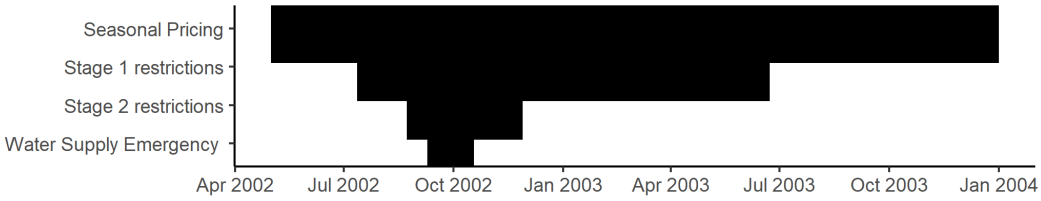
Online Appendix

C Command-and-Control (CAC) Restrictions

Figure C1: Timeline of CAC Restriction Implementation



Definitions of stage restrictions provided in April 2002

- **Stage 1:** Irrigation of lawns, gardens, trees, or shrubs with OWASA-supplied potable water applied through any system or device other than a hand-held hose or watering can shall be allowed only three days out of each week.
- **Stage 2:** Irrigation of lawns, gardens, trees, or shrubs with OWASA-supplied potable water applied through any system or device other than a hand-held hose or watering can shall be allowed only one day out of each week.
- **Emergency:** No OWASA-supplied potable water for any outdoor purposes other than emergency fire suppression or other activities necessary to maintain public health, safety, or welfare.

Modifications of CAC policies in June 2003

- **Year-Round Conservation Requirement:** Spray irrigation limited to 3 days/week. Use of reclaimed or harvested water strongly encouraged. Use of water saving fixtures strongly encouraged. Unless superceded by the declaration of a Water Supply Shortage or Emergency, this requirement did not apply to outdoor irrigation necessary for the establishment of newly sodded lawns and landscaping within the first 30 days of planting, or watering of newly seeded turf within the first six months of planting.

D Sensitivity Analysis: Usage Profile Assignment

In the main paper, we defined households in terms of their usage profile observed during the year prior to treatment, October 2000-September 2001. Here we consider an alternative specification in which households are defined in terms of their usage profile observed during October 1999-September 2000.

Table D1 shows the results of estimating (1) using the usage profiles observed during October 1999-September 2000. We find that the main estimation results are robust to which pre-treatment year is used to assign usage profiles.

Table D1: Main Results, Different Reference Year

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	0.0367	-0.0177	-0.0740	-0.1681
	(0.0340)	(0.0076)	(0.0152)	(0.0133)
Low wealth, moderate usage	-0.1970	-0.0530	-0.0859	-0.2114
	(0.0331)	(0.0073)	(0.0136)	(0.0126)
Low wealth, heavy usage	-0.4655	-0.0909	-0.0855	-0.3026
	(0.0636)	(0.0177)	(0.0301)	(0.0323)
High wealth, light usage	0.0600	-0.0146	-0.0752	-0.1842
	(0.0401)	(0.0098)	(0.0220)	(0.0181)
High wealth, moderate usage	-0.1680	-0.0319	-0.0734	-0.2487
	(0.0297)	(0.0058)	(0.0127)	(0.0108)
High wealth, heavy usage	-0.4239	-0.0575	-0.0569	-0.4374
	(0.0607)	(0.0092)	(0.0197)	(0.0211)

Note: Other than the assignment of households to usage groups, the estimated model matches the one reported in Table C1 Panel A. The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. In addition to the variables displayed in this table, the model includes a dummy variable for the post-seasonal pricing period and interactions of usage type and wealth indicators with: water stress, temperature, log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage. Standard errors, clustered at the household level, are in parentheses.

Table D2 shows the year-to-year transitions starting with October 1999-September 2000. The percentages are similar to those presented in Table 3.

Table D2: Transition in Usage Profiles, Different Reference Year

Panel A	All Households *(N=4455)*								
Oct99-Sep00	*Light (N=1508)*			*Moderate (N=2181)*			*Heavy (N=766)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct00-Sep01	0.81	0.19	0.00	0.11	0.82	0.07	0.01	0.31	0.68
Oct01-Sep02	0.77	0.22	0.01	0.15	0.74	0.11	0.02	0.31	0.68
Oct02-Sep03	0.88	0.12	0.00	0.35	0.62	0.03	0.09	0.57	0.33
Oct03-Sep04	0.85	0.14	0.01	0.32	0.62	0.06	0.06	0.52	0.42
Oct04-Sep05	0.83	0.16	0.01	0.32	0.63	0.05	0.08	0.51	0.42
Panel B	Lower Wealth Households *(N=2080)*								
Oct99-Sep00	*Light (N=1005)*			*Moderate (N=886)*			*Heavy (N=189)*		
Oct00-Sep01	0.86	0.13	0.00	0.15	0.80	0.05	0.03	0.37	0.60
Oct01-Sep02	0.84	0.16	0.00	0.19	0.73	0.08	0.03	0.42	0.55
Oct02-Sep03	0.90	0.10	0.00	0.39	0.59	0.02	0.13	0.58	0.29
Oct03-Sep04	0.88	0.12	0.00	0.36	0.59	0.05	0.09	0.57	0.34
Oct04-Sep05	0.87	0.12	0.00	0.36	0.60	0.03	0.15	0.57	0.28
Panel C	Higher Wealth Households *(N=2375)*								
Oct99-Sep00	*Light (N=503)*			*Moderate (N=1295)*			*Heavy (N=577)*		
Oct00-Sep01	0.70	0.30	0.00	0.09	0.83	0.08	0.01	0.29	0.71
Oct01-Sep02	0.65	0.33	0.02	0.13	0.74	0.13	0.01	0.27	0.72
Oct02-Sep03	0.84	0.16	0.00	0.32	0.64	0.04	0.08	0.57	0.35
Oct03-Sep04	0.80	0.19	0.01	0.29	0.65	0.06	0.05	0.50	0.45
Oct04-Sep05	0.76	0.23	0.01	0.29	0.65	0.06	0.05	0.49	0.46

Note: The table above shows the proportion of users of in each initial usage profile whose consumption best matches each profile in the subsequent four years.

E Water Stress vs. Traditional Environmental Controls

In this section, we assess the goodness of fit for models using different sets of environmental controls. We compare the main set of results, using a Block Group-level water stress index, to models using collections of weather variables. We obtained data for weather variables from the NC Climate Office for the Chapel Hill-Williams Airport weather station. We estimate models using the following sets environmental of controls:

- Collection 1: Total precipitation and average temperature
- Collection 2: Total precipitation, lagged total precipitation, average temperature, lagged average temperature
- Collection 3: Total precipitation, total precipitation squared, number of days with no rain, average temperature
- Regional Water Stress and average temperature
- Census Block Group Water Stress and average temperature

We do not include NDVI in our comparison models, as the area of study is not well suited for use because the coarse resolution of the satellite images (30m x 30m) is not precise enough to discern landscapes on individual parcels in the study area. Aside from typically small parcel sizes, tree cover is prevalent, and the area is relatively wet, therefore cloud cover obstruction frequently results in unusable images.[31]

We assess model fit based on deviations in prediction accuracy using several model evaluation scores. We provide scores for root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) in Table E1. The errors provided in the table are based on differences between actual and predicted values and smaller errors reflect more accurate predictions. Scores differ in how large errors are treated. RMSE

[31]NDVI particular useful in areas such as the western United States, regions where parcel sizes are relatively large, climate is arid and hence experience few cloudy days, and tree cover sparse. https://earthexplorer.usgs.gov/

gives extra weight to large errors whereas MAPE and MAE give equal weight to all errors. MAPE differs from the other two metrics in that is scores are in terms of percentages and are therefore scale-independent. The results suggest that using water stress leads to minor improvements in model fit.

Table E1: Goodness of Fit Results

Environmental Model	RMSE	MAPE	MAE
Collection 1	39.452	27.641	28.702
Collection 2	39.322	26.205	28.584
Collection 3	39.145	28.265	28.492
Water Stress Regional	38.723	23.241	28.175
Water Stress Block Group	38.778	25.349	28.204

Notes: All models include average temperature. RMSE: Root mean square error, MAPE: Mean absolute percentage error, MAE: Mean absolute error

Estimation Results for Alternative Environmental Controls

Tables E2 through E5 contain results from models with alternative environmental controls. The results are qualitatively similar to the main estimation results, with a few small differences. Specifically, the alternative environmental controls produce lower price sensitivity among wealthier households with *Moderate* and *Light* usage profiles, although the differences are smaller in the models with more complex collections of weather variables. Our findings suggest that collections of weather variables in relatively wet climate areas similar to the area of study may be used in water demand estimation studies without the introduction of too much measurement error. Future research, however, is needed to test the robustness of this measure in the context of different climates.

The most common combination of weather variables used as environmental controls is *Collection 1*. Using these measures results in price elasticity estimates that are qualitatively similar though smaller in magnitude to those found when using water stress.

Table E2: Main Results with Collection 1 Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	0.1153	0.0186	-0.0676	-0.1173
	(0.0288)	(0.0075)	(0.0148)	(0.0130)
Low wealth, moderate usage	-0.0568	-0.0352	-0.0863	-0.1909
	(0.0365)	(0.0067)	(0.0127)	(0.0130)
Low wealth, heavy usage	-0.2816	-0.0500	-0.0457	-0.1869
	(0.0526)	(0.0190)	(0.0297)	(0.0341)
High wealth, light usage	0.1236	-0.0042	-0.0440	-0.1354
	(0.0408)	(0.0097)	(0.0225)	(0.0190)
High wealth, moderate usage	-0.0199	-0.0241	-0.0549	-0.2405
	(0.0267)	(0.0055)	(0.0121)	(0.0108)
High wealth, heavy usage	-0.2213	-0.0419	-0.0384	-0.4095
	(0.0610)	(0.0096)	(0.0197)	(0.0222)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. In addition to the variables displayed in this table, the model includes a dummy variable for the post-seasonal pricing period and interactions of usage and wealth indicators with: total precipitation, temperature, log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage. Standard errors, clustered at the household level, are in parentheses.

When we include *collection 2* in the model, our price elasticity become more similar to those we obtain when using water stress.

Table E3: Main Results with Collection 2 Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	0.0739	0.0240	-0.0717	-0.1405
	(0.0292)	(0.0079)	(0.0148)	(0.0130)
Low wealth, moderate usage	-0.1087	-0.0212	-0.0871	-0.2220
	(0.0379)	(0.0071)	(0.0127)	(0.0132)
Low wealth, heavy usage	-0.3364	-0.0334	-0.0495	-0.2210
	(0.0553)	(0.0203)	(0.0306)	(0.0349)
High wealth, light usage	0.0756	0.0024	-0.0483	-0.1601
	(0.0413)	(0.0103)	(0.0225)	(0.0191)
High wealth, moderate usage	-0.0849	-0.0039	-0.0693	-0.2719
	(0.0274)	(0.0057)	(0.0120)	(0.0110)
High wealth, heavy usage	-0.3092	-0.0073	-0.0670	-0.4476
	(0.0631)	(0.0099)	(0.0200)	(0.0229)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. In addition to the variables displayed in this table, the model includes a dummy variable for the post-seasonal pricing period and interactions of usage and wealth indicators with: total precipitation, lagged total precipitation, temperature, lagged average temperature, log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage. Standard errors, clustered at the household level, are in parentheses.

Similarly, when we include *collection 3* in the model, our price elasticity estimates become more similar to those we obtain when using water stress.

Table E4: Main Results with Collection 3 Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	0.0953	0.0027	-0.0687	-0.1436
	(0.0290)	(0.0076)	(0.0154)	(0.0129)
Low wealth, moderate usage	-0.0761	-0.0417	-0.0563	-0.2069
	(0.0369)	(0.0068)	(0.0133)	(0.0129)
Low wealth, heavy usage	-0.2980	-0.0515	-0.0030	-0.1950
	(0.0532)	(0.0194)	(0.0296)	(0.0334)
High wealth, light usage	0.1063	-0.0155	-0.0485	-0.1573
	(0.0407)	(0.0097)	(0.0235)	(0.0189)
High wealth, moderate usage	-0.0317	-0.0292	-0.0303	-0.2488
	(0.0268)	(0.0055)	(0.0123)	(0.0107)
High wealth, heavy usage	-0.2259	-0.0410	0.0149	-0.4041
	(0.0610)	(0.0097)	(0.0200)	(0.0220)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. In addition to the variables displayed in this table, the model includes a dummy variable for the post-seasonal pricing period and interactions of usage and wealth indicators with: precipitation, precipitation squared, days with no rain, temperature, log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage. Standard errors, clustered at the household level, are in parentheses.

We obtain similar price elasticity estimates when we use watershed-level water stress measures versus the Block-Group-level water stress measures of our main analysis.

Table E5: Main Results with Regional Water Stress Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	0.0236	0.0039	-0.0795	-0.1587
	(0.0301)	(0.0079)	(0.0154)	(0.0129)
Low wealth, moderate usage	-0.1787	-0.0282	-0.0682	-0.2320
	(0.0398)	(0.0070)	(0.0134)	(0.0131)
Low wealth, heavy usage	-0.4156	-0.0296	-0.0203	-0.2211
	(0.0599)	(0.0206)	(0.0299)	(0.0342)
High wealth, light usage	0.0114	-0.0132	-0.0658	-0.1692
	(0.0423)	(0.0102)	(0.0233)	(0.0190)
High wealth, moderate usage	-0.1586	-0.0109	-0.0490	-0.2693
	(0.0287)	(0.0056)	(0.0122)	(0.0107)
High wealth, heavy usage	-0.3982	-0.0018	-0.0015	-0.4301
	(0.0653)	(0.0099)	(0.0199)	(0.0223)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. In addition to the variables displayed in this table, the model includes a dummy variable for the post-seasonal pricing period and interactions of usage and wealth indicators with: regional water stress, temperature, log(read days), and a nonlinear intra-year time trend. The model also includes linear inter-year time trends for summer and non-summer usage. Standard errors, clustered at the household level, are in parentheses.

F Transitions in Usage Profiles By Wealth

In this section we provide information on the fraction of households that transition in usage profiles by household wealth. Transitions are qualitatively similar to that observed for the entire sample with the exception that significant decreases in usage in transitioning from *Heavy* to *Light* are more commonly observed among low-wealth households than high-wealth households.

Table F1: Transitions in Usage Profiles

Panel A	All Households *(N=4455)*								
Oct00-Sep01	*Light (N=1481)*			*Moderate (N=2301)*			*Heavy (N=673)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct01-Sep02	0.82	0.17	0.00	0.12	0.76	0.11	0.01	0.24	0.75
Oct02-Sep03	0.89	0.11	0.00	0.35	0.62	0.03	0.05	0.56	0.39
Oct03-Sep04	0.86	0.13	0.01	0.31	0.63	0.06	0.04	0.49	0.46
Oct04-Sep05	0.85	0.14	0.01	0.31	0.64	0.06	0.06	0.49	0.44
Panel B	Lower Wealth Households *(N=2080)*								
Oct00-Sep01	*Light (N=1003)*			*Moderate (N=912)*			*Heavy (N=165)*		
Oct01-Sep02	0.87	0.13	0.00	0.15	0.77	0.07	0.02	0.35	0.63
Oct02-Sep03	0.90	0.10	0.00	0.40	0.57	0.02	0.06	0.60	0.34
Oct03-Sep04	0.88	0.12	0.00	0.36	0.59	0.05	0.04	0.56	0.39
Oct04-Sep05	0.88	0.12	0.00	0.36	0.61	0.03	0.10	0.57	0.33
Panel C	Higher Wealth Households *(N=2375)*								
Oct00-Sep01	*Light (N=478)*			*Moderate (N=1389)*			*Heavy (N=508)*		
Oct01-Sep02	0.74	0.26	0.01	0.10	0.76	0.14	0.00	0.20	0.79
Oct02-Sep03	0.87	0.12	0.00	0.32	0.65	0.03	0.05	0.55	0.40
Oct03-Sep04	0.82	0.17	0.01	0.28	0.65	0.07	0.05	0.47	0.48
Oct04-Sep05	0.79	0.19	0.01	0.27	0.65	0.07	0.05	0.47	0.48

Note: The table above shows the proportion of users of in each initial usage profile whose consumption best matches each profile in the subsequent four years.